Real-Time Decision System Customer Perceived Value (Cpv) Via Internet of Things (Iot) and Explainable Ai (Xai)

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Abstract:
SMEs in today's increasingly competitive business world must know, in real-time, what customers genuinely value and respond accordingly. However, conventional methods of quantifying Customer Perceived Value have utilized surveys and historical data, which are slow, subjective, and unable to access real-time customer sentiment. It is proposed that this paper create a real-time framework that combines the Internet of Things and Explainable Artificial Intelligence to predict and explain CPV at any time. The use of RFID tags and production sensors will enable IoT devices to capture data on customer–product interactions. This analysis, combined with artificially intelligent software that renders inferences about the data, will allow a Random Forest model to forecast CPV. In this instance, artificially intelligent forecasts will not be black-boxed. Instead, I utilize the SHAP and LIME techniques to render each forecast comprehensible. The predictive model and the customers update the forecast, and one can understand what causes a high or low-perceived value at any given moment. Thus, the framework will offer feedback. That is, extraction from the explanation process has the potential to affect change. These insights guide the collection of managerial activities that will drive adjustments in customer behaviors and thus their forecast. This integrated use of the IoT and XAI not only improves prediction accuracy but also establishes managerial confidence, resulting in decentralized, data-driven decision-making. SMEs can subsequently take that technique and become responsive to proactive action, enhancing overall transparency and real-time analytics.

Keywords: Internet of Things (IoT), Explainable Artificial Intelligence (XAI), Customer Perceived Value (CPV), Small and Medium-sized Enterprises (SMEs), Machine Learning (ML), Real-time Analytics, SHAP, LIME, Predictive Modeling, Transparent Decision-Making, Customer Behavior, Value Co-Creation.

1. INTRODUCTION

In the age of digital transformation, small and medium-sized businesses (SMEs) come under increasing pressure to comprehend the customer, respond quicker to market shifts, and provide value in a consistent manner. With access to sophisticated analytics and big data infrastructures typically available only to big corporations, SMEs have limited capabilities and no stamina to relentlessly track real-time truths about customer perceptions and behaviors. One of the highest and most intricate facets of business performance in this context lies in Customer Perceived Value (CPV) — the overall value judgment a customer makes on the product or service based on what they receive compared to what they provide. Conventional approaches to gauging CPV, such as surveys or post-consumption interviews, take a long time, are subjective, and reactive. They do not accurately depict the ongoing and ever-changing nature of customer value perception in real-world settings.

These new Internet of Things (IoT) and Artificial Intelligence (AI) innovations have opened up new avenues for decisions based on real-time data-based decision-making. Internet-of-Things-enabled devices such as RFID tags, sensor-based production systems, and Internet-of-Things-enabled products have the potential to enable the capture of continuous behavioral and operational data that emulate customer interaction patterns and usage experiences. Using such data with the help of Machine Learning (ML) models, organizations can make predictions of shifts in customer value perception and make proactive decisions on operations, prices, and marketing strategies. But the fundamental big challenge remaining is this: even though ML algorithms make accurate predictions, they have a tendency to act like "black boxes" and shed no light on how and why such predictions are being generated. This explainability shortfall undermines managerial confidence, inhibits adoption, and brings with it associated ethical and operational risks, especially in small organizations where decision-makers need clear, interpretable results. To address these issues, this study introduces an integrated IoT–XAI framework to provide real-time CPV prediction and explanation in a format suitable for SMEs. The framework trains CPV prediction-based ML models, such as in this case a Random Forest model, on IoT data streams, and Explainable AI (XAI) methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are used to explain the reasoning behind each prediction. This amalgamation not only increases predictive precision but also increases explainability to enable SME managers to understand the most potent influencers of customer perceptions at any given moment.

These research's main targets have three folds:

1. To construct an in-real-time prediction pipeline that exploits IoT data to dynamically estimate CPV;
2. To apply XAI techniques to interpret and visualize the driving factors of CPV forecasts; and
3. To present a decision-support framework that allows SMEs to provide explainable, transparent, and customer-centric business decisions.

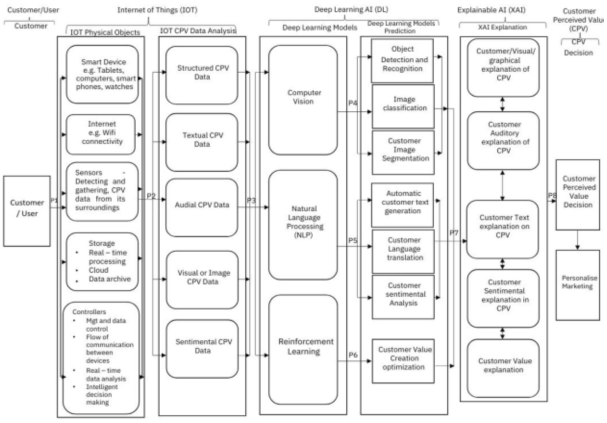
By combining data produced by IoT with explainable AI models, our work attempts to narrow the chasm between predictive intelligence and human understanding—driving SMEs toward value-based, explainable, and proactive business strategies rather than reactive ones.

2. LITERATURE REVIEW

[1] Research paper "The role of IoT and XAI convergence in the prediction, explanation, and decision of customer perceived value (CPV) in SMEs: a theoretical framework and research proposition perspective" by Kwabena Abrokwah-Larbi was published in Discover Internet of Things in 2025. It focuses on the Internet of Things (IoT)-Explainable AI (XAI) convergence framework to make Customer Perceived Value (CPV) a strategic asset in Small and Medium-sized Enterprises (SMEs). A customer interaction with IoT devices generating data and then fed to Deep Learning models to predict CPV and then explained with the help of XAI model's workflow is described in the proposed theoretical framework. This yields actionable CPV decision-making with explainability and optimized personalized marketing. It has the disadvantage of being a conceptual model to still be empirically tested and potential implementation

challenges in SMEs with limited resources. It was built upon an extensive review of customer-IoT interaction literature, IoT data analysis, deep learning, and XAI literature.

[2] In the research paper "Transforming Business Decision Making with Internet of Things (IoT) and Machine Learning (ML)", authored by Mahmood Asad Moh'd Ali, Yonma Abdulla, Abu Basahr, and Mustafa Raza Rabbani, presented at the International Conference on Decision Aid Sciences and Application (DASA) in 2020, the paper emphasizes combining IoT and Machine Learning (ML) to improve real-time data-based decision-making in several sectors of business. The architectural model proposed consists of a four-step process comprising connectivity of devices, data aggregation and analysis, visualization in the form of dashboards, and a feedback loop to enable correctives. It illustrates tangible uses in manufacturing to perform predictive maintenance, in drugs to track supply chains, and in hotels to provide personalized guest experiences. In its weaknesses, it identifies recognized shortcomings in the form of technological challenges, security weaknesses in networks, and interoperability with existing legacy systems, and fails to mention interpret ableness in the resultant ML models itself. Conceptual discussions were presented on the basis of its potential in several industry segments.



[3] The research paper titled 'Advanced supply chain analytics: Leveraging digital twins, IoT and blockchain for resilient, data-driven business operations' was authored by Louis Owusu-Berko and published in the World Journal of Advanced Research and Reviews in February 2025. It focuses on how Digital Twins, the Internet of Things (IoT), and Blockchain can be used in advanced supply chain analytics to build resilient, data-driven businesses and tackle challenges like demand fluctuations and logistical inefficiencies. As a review article, its Methodology involves examining the existing literature, industry, applications, and future potential of these integrated technologies. The paper posits that this integration enables real-time supply chain optimization, proactive risk management, and a shift from reactive to predictive decision-making. Its flaws or challenges, as identified in the paper, include the complexities of data standardization, system integration, and significant cybersecurity risks that must be addressed for successful implementation. The paper concludes by providing strategic insights on how businesses can use these technologies to enhance agility and reduce operational costs.

[4] The research paper titled 'Big Data Analytics and IoT in logistics: a case study' was authored by John Hopkins and Paul Hawking and published in The International Journal of Logistics Management in 2018. It focuses on documenting the real-world impact of Big Data Analytics (BDA) and the Internet of Things (IoT) on a large logistics company's strategy to improve driver safety, reduce costs, and minimize environmental impact. The methodology employed was a single intrinsic case study of a company that used truck telematics (IoT) to monitor driver behavior, along with camera-based systems like "Truckcam" and "Drivercam" for safety and fatigue management. The study found that this approach led to a significant

reduction in accidents and a 42% decrease in GHG emissions, largely due to changes in driving behavior. Limitations of the research include that its findings are based on a single case and may not be broadly generalizable. The case study confirmed the effectiveness of these technologies, as BDA was used to create congestion maps for route optimization and telematics data helped exonerate a driver in a fatal accident investigation.

[5] The research paper titled 'The Role of AI in Driving Accountability and Transparency in Global Supply Chains: The Fragmented Bridge Between Research and Practice' was authored by Boutayna Elghomri, Fayçal Messaoudi, and Nihal Touti and published in Operations and Supply Chain Management in 2025. It focuses on examining how Artificial Intelligence (AI) enhances accountability and transparency in global supply chains, while also highlighting the significant gap between academic research and practical industry implementation. The methodology involved a comprehensive bibliometric analysis of 421 peer-reviewed articles using VOSviewer to visualize networks and identify thematic clusters. The analysis revealed exponential growth in research after 2020 and identified four key research streams: foundational AI technologies (IoT, blockchain), AI-driven decision-making, AI-blockchain integration, and AI-IoT synergy for sustainability. The primary flaw identified is the disconnect between theory and practice, with findings showing that 66% of the literature focuses on theoretical development while only 23% addresses practical implementation, leaving organizational and ethical challenges underexplored. The study concludes by calling for more integrative research that connects technological innovation with managerial practices and regulatory frameworks to bridge this gap.

[6] The research paper titled 'A comprehensive survey on AI-enabled secure social industrial Internet of Things in the agri-food supply chain' was authored by Sajal Halder et al. and published in Smart Agricultural Technology in 2025. It focuses on addressing the security, data integrity, and interoperability challenges of integrating AI with the Social Industrial Internet of Things (SIIoT) in the agri-food supply chain. The methodology involved a systematic literature review of recent peer-reviewed articles and an examination of multiple case studies, such as smart farming in an apple orchard. A key contribution is the development of a structured taxonomy for AI-driven security mechanisms, which are categorized into three layers: AI-Driven Automation, Secure IoT Infrastructure, and Cybersecurity and Trust Management. The survey found that AI solutions significantly enhance trust, anomaly detection, and data privacy in these networks. The paper identifies a gap in current research regarding emerging threats from Generative AI and the secure integration of Large Language Models (LLMs) in the agri-food sector.

[7] The research paper titled 'BUSINESS GROWTH ANALYSIS THROUGH PREDICTIVE AI' was authored by Abhiram Bikki, Naga Sandeep Bande, and Tanush Yedla and published in the JAAFR Journal of Advance and Future Research in April 2025. It focuses on using predictive analytics to analyze sales data from service-based establishments to help new entrepreneurs identify high-demand products in specific regions. The proposed methodology involves collecting and preprocessing historical sales data, using Exploratory Data Analysis (EDA) to find patterns, and training machine learning models like Random Forest and Gradient Boosting to forecast demand. This data-backed system provides entrepreneurs with region-specific recommendations, helping to reduce uncertainty and improve product-market fit. While not explicitly stated, a potential limitation is the model's reliance on the quality of historical data and its ability to adapt to sudden market shifts. The model's effectiveness was evaluated on two different products, achieving high average accuracies of 97.26% and 98.68% respectively, outperforming traditional forecasting methods.

[8] The research paper titled 'Internet of Things (IoT) in logistics' was authored by Galina V. Ivankova,

Ekaterina P. Mochalina, and Natalia L. Goncharova and was published in the IOP Conference Series: Materials Science and Engineering in 2020. It focuses on the application and impact of IoT in the logistics industry as part of the industry 4.0 revolution. The methodology is a review that explores real-world examples, such as Amazon's use of warehouse robots for automation, the use of drones for last-mile delivery, and vehicle tracking systems for fleet management. The paper highlights that IoT enables real-time asset tracking, automates manual tasks, reduces operating costs, and improves security against theft. Its flaws and challenges include a lack of universal IoT standards, significant cybersecurity risks, and practical limitations for technologies like drones, such as vulnerability to weather and legal restrictions. The paper concludes that while IoT has massive potential, its adoption requires overcoming these obstacles and shifting business mindsets toward optimizing logistics flows.

[9] The research paper titled 'Automation of business processes of the logistics company in the implementation of the IoT' was authored by Oksana Ilyashenko et al. and published in the IOP Conference Series: Materials Science and Engineering in 2020. It focuses on analyzing and improving the process of monitoring the technical condition of railway vehicles at a logistics company to reduce financial losses from downtime. The methodology involved modeling the existing manual inspection process ("as is") and then designing an automated "to be" process using IoT technology integrated with an Enterprise Asset Management (EAM) system. In the proposed system, IoT sensors are used for real-time, automated diagnostics to enable predictive maintenance and avoid unnecessary vehicle downtime. The advantage of this approach is that it reduces repair times and improves operational planning. The paper is conceptual and presents a new process model as its primary result, outlining potential benefits like cost savings and enhanced safety without providing quantitative data from a real-world implementation.

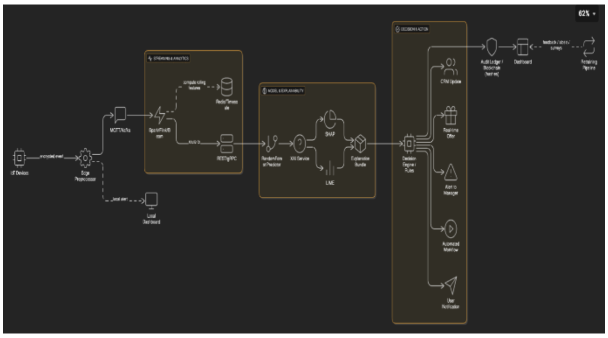
[10] The research paper titled 'Explaining machine learning models in sales predictions' was authored by Marko Bohanec, Mirjana Kljajić Borštnar, and Marko Robnik-Šikonja and published in Expert Systems with Applications in 2017. It focuses on solving the problem that highly accurate "black-box" machine learning models are often avoided in business because their decision-making is not transparent. The proposed methodology utilizes general explanation techniques (EXPLAIN and IME) to interpret the predictions of any ML model, decomposing a prediction into the individual contributions of each attribute. This allows users to understand the reasoning behind a model's forecast and conduct "what-if" analyses to evaluate different scenarios. This approach allows businesses to use the best-performing models without sacrificing interpretability. Its limitations include the fact that explanations are only as reliable as the underlying model, and the more advanced IME method can be computationally slow. In a real-world B2B sales forecasting case, the Random Forest model achieved 78.2% accuracy, and the paper effectively demonstrated how the explanation tools could be used to analyze sales deals and support strategic decision-making.

[11] The research paper titled 'IoT and Big Data Analytics: Revolutionizing Business and Society with Advanced Insights' was authored by Sadi Badi and published in the International Journal of Applied Mathematics and Computer Science in February 2024. It focuses on the synergistic and transformative impact of combining the Internet of Things (IoT) and Big Data Analytics on businesses and society. The paper is a review that provides an overview of IoT components (sensors, connectivity, edge/cloud computing) and Big Data analytics techniques (descriptive, predictive, prescriptive). It explains how data from IoT devices is collected and processed to enable real-time, data-driven decision-making. The paper claims this integration enhances operational efficiency, creates new business models, and offers societal benefits in areas like healthcare and smart cities. The primary challenges discussed are the "digital divide,"

which widens disparities in technology access, and significant ethical and privacy concerns regarding the vast amount of data collected. The paper illustrates its points with successful case studies from companies like General Electric and Amazon.

[12] The research paper titled "The Business Value of IoT and Big Data Analytics" was authored by Waseem Ullah Khan and published in the Journal of Business and Management Studies (JBMS) in February 2025. It focuses on the disruptive impact of combining the Internet of Things (IoT) and Big Data Analytics on business models, particularly how they enable data-driven decision-making, operational efficiency, and innovation. The methodology is qualitative, based on a literature review and an analysis of case studies from companies like Amazon, Rolls-Royce, and Siemens across retail, healthcare, manufacturing, and logistics. The paper shows that this technological integration allows businesses to shift from product-based to service-based models, such as Rolls-Royce's "Power by the Hour," and gain a competitive advantage through process optimization and cost reductions. The flaws and challenges identified include significant data security risks, as IoT devices are vulnerable to cyber-attacks, high implementation costs that are a barrier for smaller businesses, and a notable skills gap in data science and cybersecurity. The research found that companies that successfully deploy these technologies see quantifiable returns; for instance, GE reduced its maintenance costs by 20% by using IoT-based predictive maintenance.

[13] The research paper titled "AI-DRIVEN IOT AND BLOCKCHAIN INTEGRATION IN INDUSTRY 5.0 A SYSTEMATIC REVIEW OF SUPPLY CHAIN TRANSFORMATION" was authored by Bhanu Prakash Sah et al. and published in the Innovatech Engineering Journal in 2024. It focuses on the transformative potential of integrating Artificial Intelligence (AI), the Internet of Things (IoT), and Blockchain in supply chain management within the human-centric framework of Industry 5.0. The methodology employed was a systematic review adhering to PRISMA guidelines, which analyzed 120 peer-reviewed articles published between 2018 and 2024. The study highlights that the convergence of these technologies enhances decision-making with predictive analytics, provides real-time monitoring via IoT, and fosters trust and security through Blockchain's decentralized ledger. Its identified flaws and barriers to adoption include issues with scalability (particularly for Blockchain), a lack of interoperability between different systems, and organizational resistance to change. The review's findings showed that, out of the 120 articles, 75 detailed significant improvements in operational efficiency, 58 examined how Blockchain enhances transparency, and 63 highlighted the role of these technologies in meeting Environmental, Social, and Governance (ESG) compliance goals.



[14] The research paper titled "Revolutionizing Business Intelligence: Integrating Big Data, AI, Machine Learning, IoT, and Blockchain for Smarter Decision-Making" was authored by Tobiloba Kollawole Adenekan and published in February 2025. It focuses on how the convergence of Big Data, AI, Machine Learning (ML), IoT, and Blockchain can enhance modern Business Intelligence (BI) systems to support

more proactive and intelligent decision-making. The research used a mixed-methodology, combining a systematic literature review with qualitative data from structured interviews with BI experts and case study analyses. The paper argues that this integration allows for improved predictive analytics, real-time data collection, and secure, transparent transactions, transforming BI into a powerful strategic tool. The study identifies several flaws and challenges, including scalability issues, lack of interoperability with legacy systems, data privacy concerns that require compliance with regulations like GDPR, and high implementation costs that are particularly difficult for SMEs. Empirical findings from the research showed that AI-driven BI systems can lead to a 140% improvement in data processing speed and a 26% increase in predictive accuracy compared to traditional BI systems.

3. RESEARCH GAP

Whilst IoT and AI technologies have been extensively studied in separation, there is a glaring void in integrated, real-time systems that utilize IoT-generated data streams to forecast Customer Perceived Value (CPV) and also explain the logic behind such forecasts. Most existing frameworks either center on operational efficiency enhancement with IoT data or predictive accuracy enhancement with ML algorithms, while neglecting value-added explainability and transparency in managerial decisions. This void is even more prevalent in SMEs, where the managers require real-time actionable knowledge that so happens to be both accurate and comprehensible. Existing CPV assessment approaches are static and post-hoc, based on episodic surveys instead of real-time behavioral data. Meanwhile, existing AI models, while potent, alas act like "black boxes," undermining managerial confidence and adoption. There is hence a pressing need to develop a real-time IoT–XAI convergence framework that periodically gathers data with IoT sensors, predicts CPV with ML algorithms, and utilizes XAI methods such as SHAP and LIME to decipher these forecasts in humanly interpretable terms—so that SMEs could make proactive, transparent, and value-based business decisions.

In the past decade, researchers and practitioners have investigated the adoption of the Internet of Things (IoT) and Artificial Intelligence (AI) to improve operational effectiveness and customer experience in a wide range of sectors. Whereas IoT technologies allow the ongoing collection of behavioral and environmental data, Machine Learning (ML) methods make it possible for organizations to identify latent patterns and make estimations on future trends. A fundamental void still exists in how these technologies are utilized in combination to comprehend and optimize Customer Perceived Value (CPV) in small and medium-sized businesses (SMEs).

Current works center around only three streams: (1) process improvement based on data acquisition with the help of IoT, (2) customer behavior prediction with predictive analytics based on ML, and (3) Explainable Artificial Intelligence (XAI) to enhance the interpretability of AI-based systems. But very few works look at combining these streams in a single real-time framework predicting and explaining and optimizing CPV in real-time. In most of the works, IoT was considered only as a data source and XAI was considered only in the form of a distinct interpretability tool and not in the scenario of a real-time continuous decision-support framework.

In addition, existing CPV models in both research and practice highly depend on subjective customer feedback measures like customer surveys or satisfaction ratings that shed limited light on contextual or behavioral value-perception affecting factors. Traditional methods are reactive and not preventive and do not record real-time changes in customer experiences. But AI-based prediction models leveraging IoT data generally present black-box systems that give little indication on how the predictions have been made.

This explainability limitation hinders managerial confidence, accountability, and AI-based decision adoption—especially in SMEs, with non-technically trained managers who make decisions. This second gap lies in the non-existence of trust and transparency systems that link predictive outputs to human decision-making on the business level. Smaller businesses have no possibility to put data science teams to work to decipher results from systems based on AI, and therefore they require interpretable, affordable solutions that link to managerial decision-making processes. Little research was conducted so far with an empirical and theoretical foundation on how XAI could close this gap and provide explainable human-based decision-making due to predictions based on IoT.

Therefore, the global market urgently requires an enterprise-wide, real-time confluence framework of IoT–XAI that forecasts customer value based on real-time interaction and sensor data and interprets the rationale of each such prediction in actionable and interpretable terms. With such a framework, SME decision-makers will also be confident in AI systems, understand customer behavior in finer detail, and foretell and formulate strategies to realize maximum customer value.

filling this void, this research introduces and tests a real-time predictive-explanatory model spanning IoT data gathering, CPV forecasting with the assistance of ML, and interpretability on the basis of XAI—providing predictive precision and human-centric explainability to allow trusted data-based business decisions in SMEs.

4. METHODOLOGY

System Architecture Overview

Four basic levels make up the outlined framework of IoT–XAI, each of which processes a majority phase in the prediction–explanation cycle (Fig. 1 depicts the workflow conceptually):

IoT Data Acquisition Layer

It collects real-time information from enabled devices like RFID tags, production gauges, point-of-sale (POS) units, and warehouse tracking systems. These data contain several parameters which affect CPV such as product performance, lead age, stock level, climatic conditions (temperature, humidity), and customer interaction rate. Data is transmitted securely using MQTT or HTTPS protocols to a cloud-based storage platform for further processing.

Data Processing and Feature Engineering Layer

Preprocessing of gathered data is performed to reduce noise, treat missing data, and attribute normalization. Time features (hourly sales rate, inventory turnover) and contextual features (promotional event, seasonally based demand) are generated. Feature Engineering Methods: rolling averages, aggregation in a time-window, and categorical encoding. Processed data gets saved into a feature store in such a manner that the predictive model always consumes it.

ML-Based CPV Prediction Layer

It uses a Random Forest model to make Customer Perceived Value (CPV) scores in real-time based on inputs from IoTs. Why Random Forest: High precision, resistance to overfitting, and aptness to heterogeneous numeric–categorical IoT data. Model Output: Each instance is assigned a CPV score ranging from 0 (low perceived value) to 1 (high perceived value). The model gets regularly refined based on new streams of incoming data to adapt to evolving customer behavior. Explanation Layer XAI (Integration of LIME and SHAP) To overcome the “black box” nature of ML, two complementary XAI techniques—SHAP and LIME—are applied:

SHAP (SHapley Additive exPlanations): Offers global and local feature importance, which informs how

much each of the IoT feature contributes to predicting the CPV.
LIME (Local Interpretable Model-Agnostic Explanations): Offers human-interpretable, simplified explanations of single predictions by approximating the model via a local linear model.
These explanations also appear on a manager's decision dashboard with, for example, "Recent sales increase (+0.25)" or "Stock shortage(+0.15)" flagged as number one driver of high CPV. It boosts manager confidence and supports human-in-the-loop decisions.

Decision and Feedback Layer
Forecasting and commentary flow into a decision-support center where SME managers may see real-time trends, drivers, and confidence levels in visualization format. Depending on the results, such decisions as price adjustments, restocking stock, or launching specialized campaigns of advertising might be made. Manager feedback or end-user outcomes (e.g., actual buy, satisfaction level) are tracked and fed into the model to retune it—completing the feedback loop to allow ongoing improvement.

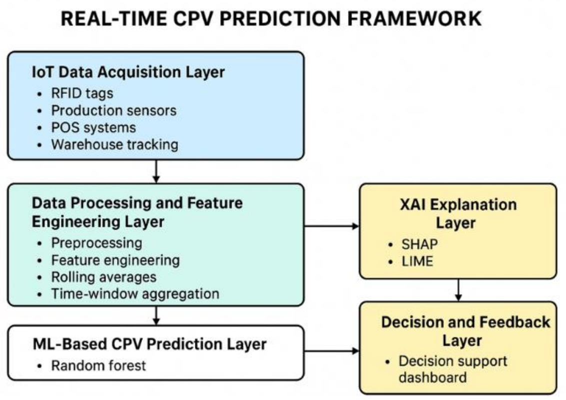


Fig1. Depicts the workflow conceptually

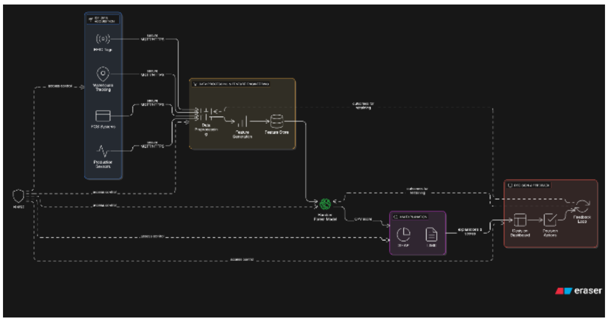
A. Real-Time Forecasting Workflow of CPV

IoT devices get real-time operational and interaction data from manufacturing, warehouse, and customer touchpoints. Data gets passed to the processing module, cleaned up, and transformed into useful feature sets The Random Forest model estimates the CPV score of each product–customer–time combination. SHAP and LIME modules explain the prediction and point out the strongest contributors. Results and explanations are shown on a dashboard, enabling real-time managerial comprehension. Manager actions (e.g., restocking, promotions) are monitored, and results make end-of-period model performance tuning possible. This real-time feedback loop guarantees that forecasts adapt with true business behavior so that the system becomes explainable, adaptive, and in practice helpful.

B. Data Description and Sources

To validate the model that has been put forth, an open retail and manufacturing IoT dataset will be taken up, like the Kaggle "Supply Chain Forecasting Dataset." This dataset comprises time-series data on product flow, inventory, demand, and climatic parameters. Real-time updates will be simulated with synthetic IoT streams to mimic operational SME scenarios. Each row will have: Product ID, Time Stamp, and Location Stock level, transaction level, and distribution frequency Sensor data (energy usage, humidity, temperature) Context data (screen name, feedback score) This rich blending of front-end and operational attributes becomes the foundation upon which learning patterns affect value that's perceived.

C. Evaluation Metrics



Technical and managerial performance measures will also be employed to assess the framework:
Prediction Accuracy: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 to define model reliability in numbers.
Explainability Quality: SHAP value stability, local LIME explanations faithfulness, and manager-assigned interpretability (Likert scale).
Real-Time Optimization: Average latency between data acquisition and display on the dashboard (target <3 seconds).
Decision Impact: Enhanced stock turnover, avoiding overproduction, and added customer satisfaction indicators.

D. Foreseen Outcomes

The future model of convergence between XAI and IoT shall bear the below results: Real-time understanding of CPV dynamics through continuous IoT data collection. Transparent decision-making, such that explained by SHAP and LIME how each CPV prediction happens. Enhanced adoption and confidence in AI in SMEs, so that non-technical managers could make data-based decisions with confidence. Adaptive business intelligence, in which the model's predictions adjust to changes in customer behavior and working conditions. Ultimately, the framework seeks to change SMEs from reactive data users to proactive insight businesses that continuously improve customer value by opening up and learning.

5. CONCLUSION

This study introduces a combined framework to affordably predict real-time Customer Perceived Value (CPV) that synthesizes the Internet of Things (IoT), Machine Learning (ML), and Explainable Artificial Intelligence (XAI) strengths. This model fills a longstanding SME decision-making gap by turning conventional, questionnaire-based CPV measurement into an ongoing, data-based, and interpretable process. Real-time operational and behavioral data can be gathered constantly with the help of IoT sensors and devices and then predicted to evolving customer value perceptions by the ML part, which has been designed using a Random Forest algorithm.
What makes this framework unique is that it integrates XAI methods, in this case, LIME and SHAP, to make each prediction traceable and interpretable. With these approaches, company managers could comprehend the rationale that underpins the outputs of the model, and that assists in building confidence and trust in decisions that rely on artificial intelligence. By explaining what the system predicts and why it predicts it, the model closes the gap between the automation and the interpretation by human beings and builds an open collaborative decision process.

It becomes a feasible road to proactive and customer-oriented strategies for small and medium enterprises. Managers can respond in real-time to conclusions drawn from IoT data—changing prices, production, or advertising in reaction to anticipated changes in customer sentiment—thus enhancing responsiveness, minimizing uncertainty, and improving customer satisfaction. In the longer term, the proposed framework could become a perpetual learning system where customer interaction in new data fine-tunes the predictive model and explanations guide strategic refinements. Subsequent research also has the potential to extend this research to deploying federated IoT networks, optimizing blockchain-enabled data proofing to strengthen security, and exploring multi-agent decision systems to support decentralized SME networks. Altogether, this research promotes explainable, real-time, and trusted AI solutions capable of empowering SMEs to understand, predict, and maximize customer value in the digital economy.

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