CryptoLife HYDRA-SAI Framework for Investor Decision Support

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Abstract—The extreme volatility and non-linear dynamics of cryptocurrency markets pose substantial challenges to conventional financial forecasting models, particularly during regime shifts and market shocks. This study introduces an innovative multi-layer artificial intelligence-based decision support framework – CryptoLife HYDRA-SAI – designed to simultaneously enhance predictive accuracy, adaptivity, and explainability in crypto-asset markets. The proposed dual architecture integrates a multi-agent learning network combining deep learning time-series forecasting, NLP-based sentiment analysis, synthetic data generation, and a real-time AI-driven Early Warning System. The research employs qualitative (questionnaire-based) thematic analysis, Exploratory and Confirmatory Factor Analysis, and Partial Least Squares Structural Equation Modelling on an expert sample (N≈2000) to empirically validate the framework. The results reveal a stable five-factor structure in which resilience, explainable AI, and AI-based early warning capabilities exert significant mediating effects on predictive performance. The structural model explains 61% of the variance in prediction accuracy, indicating substantial explanatory power in highly volatile financial environments. The CryptoLife HYDRA-SAI framework contributes to the advancement of cryptocurrency risk management, investor decision support, and supervisory monitoring through adaptive, auditable, and trustworthy AI-driven solutions.

Keywords: cryptocurrency market, early warning system, explainable artificial intelligence, multi-level AI architecture, resilience

JEL Codes: C45, C53, G17, G41, O33

I. INTRODUCTION

Cryptocurrencies – most notably Bitcoin – have emerged over the past decade as a novel and disruptive asset class within the global financial system and, despite their relatively short history, have exhibited extraordinary price volatility. The extreme volatility characteristic of crypto-asset markets simultaneously offers substantial profit potential for speculative investors while posing considerable risks to both individual and institutional market participants, and presents challenges for the maintenance of financial stability (Baur & Dimpfl, 2018; Karasiński, 2023). Baur & Dimpfl (2018) demonstrate that the price fluctuations of leading crypto-assets exceed by orders of magnitude the volatility observed in traditional asset classes such as equities or foreign exchange; some estimates suggest that cryptocurrency volatility may be up to ten times higher than that recorded in developed financial markets.

Within such an environment, conventional time-series analysis and volatility modelling approaches – including **A**uto**R**egressive **I**ntegrated **M**oving **A**verage (ARIMA) and **G**eneralized **A**uto**R**egressive **C**onditional **H**eteroskedasticity (GARCH)-type models (Huang et al., 2024) – provide only limited predictive performance. This is partly attributable to the fact that crypto-market price dynamics often approximate a stochastic random walk process, while structural breaks and regime shifts occur frequently (Urquhart, 2016). Moreover, crypto-assets largely lack stable fundamental valuation anchors – such as cash flows, dividends, or interest rates – that underpin the pricing of traditional financial instruments (Corbet et al., 2019).

A further distinctive feature of cryptocurrency markets is their global, 24-hour operation and the historically fragmented and uncertain regulatory environment in which they have evolved. Consequently, prices are frequently driven not by rational fundamentals but by behavioural and informational factors, including narratives, news, and memes disseminated via social media

(Shiller, 2017; Ante, 2023). Under such market structures, classical financial theories – including the strong form of the **E**fficient **M**arket **H**ypothesis (EMH) – do not hold unequivocally. A substantial body of empirical research indicates that cryptocurrency markets exhibit time-varying efficiency, with significant deviations from the conditions of perfect market efficiency observable in certain periods or for specific crypto-assets, manifesting for example in weekend effects, momentum phenomena, or arbitrage opportunities (Urquhart, 2016; Nadarajah & Chu, 2017; Karasiński, 2023). Collectively, these findings suggest that market anomalies in crypto-assets may be exploitable and that there is scope for more advanced, adaptive forecasting models capable of achieving superior predictive performance relative to traditional methods.

In recent years, **M**achine Learning (ML) – and in particular **D**eep **L**earning (DL) – techniques have assumed an increasingly prominent role in research on cryptocurrency price forecasting. Numerous empirical studies have shown that, by transcending the limitations of conventional statistical models, artificial neural networks are better able to capture the non-linearities and time-varying patterns characteristic of crypto-markets (Corbet et al., 2019). Accordingly, the literature has widely applied **R**ecurrent **N**eural **N**etworks (RNNs), **L**ong **S**hort-**T**erm **M**emory (LSTM) networks, and **G**ated **R**ecurrent **U**nits (GRUs), alongside classical ML algorithms such as support vector machines and tree-based ensemble methods (Random Forest, e**X**treme **G**radient **Boos**ting, XGBoost), to forecast the prices of Bitcoin and other leading cryptocurrencies (Katsiampa et al., 2017; Lahmiri & Bekiros, 2019).

Empirical evidence suggests that, under certain conditions, these ML-based models significantly outperform simple benchmark strategies – such as buy-and-hold – as well as traditional linear time-series models in short-term forecasting tasks (Atsalakis et al., 2019). A comprehensive comparative analysis across multiple model families concludes that state-of-the-art DL architectures, particularly GRU-based models, together with advanced ensemble algorithms such as LightGBM, consistently deliver superior predictive performance in cryptocurrency price forecasting relative to earlier methodologies and passive investment strategies (Bouteska et al., 2024; Filippou et al., 2024). The empirical investigation of Bouteska et al. (2024) demonstrates that GRU and other recurrent neural networks, as well as gradient boosting algorithms, systematically outperform conventional time-series models when applied to Bitcoin, Ethereum, Ripple, and Litecoin data, suggesting that these approaches currently represent the most effective methods for purely predictive applications.

Nevertheless, the application of DL and ML approaches is subject to several important limitations. First, model performance may deteriorate substantially in the presence of regime changes – for example, when a stable market phase is abruptly replaced by speculative mania or panic-driven sell-offs – if models are not retrained with sufficient frequency (Karasiński, 2023). Secondly, most DL models operate as "black boxes", rendering the decision-making logic underlying their forecasts opaque to practitioners, thereby significantly constraining their practical applicability in financial risk management contexts (Giudici et al., 2024). Finally, the majority of these models lack embedded early-warning mechanisms capable of explicitly signalling forecast uncertainty or the probability of impending market shocks (Walther et al., 2019). As a consequence of these structural shortcomings, financial professionals and institutional decision-makers often adopt a cautious stance towards the deployment of cutting-edge artificial intelligence-based forecasting models in live environments, particularly where decisions entail substantial financial risk.

An underexplored and insufficiently developed area within the literature on cryptocurrency market forecasting concerns the following issue: relatively few attempts have been made to design a comprehensive, multi-component artificial intelligence framework capable of simultaneously addressing the challenges of predictive accuracy, adaptivity, and explainability within the uniquely volatile and non-linear environment of crypto-markets (Bouteska et al., 2024; Giudici et al., 2024). According to Filippou et al. (2024), the majority of existing empirical studies focus either on optimising the performance of a single model architecture – such as an LSTM or GRU neural network – or, at most, combine several algorithms using conventional ensemble techniques; the application of meta-level learning or agent-based interactions to support dynamic decision-making among models remains rare.

At the same time, cryptocurrency price dynamics are shaped by numerous interacting factors. These include the trajectory of the technology adoption lifecycle – for instance, the expansion or stagnation of Bitcoin adoption – changes in the regulatory environment (including prohibitions, tax tightening, or liberalisation), fluctuations in global macroeconomic conditions, and collective investor sentiment and behaviour, frequently driven by narratives and information disseminated through social media (Corbet et al., 2019; Shiller, 2017). Owing to these multifaceted and time-varying mechanisms, reliance on a single, static model is typically insufficient for the reliable forecasting of cryptocurrency prices, particularly during regime shifts or episodes of extreme market stress (Karasiński, 2023).

The problem of volatility forecasting is further complicated by the dynamic evolution of cryptocurrency markets. Distinct patterns may prevail at different stages of the market lifecycle. For example, during the launch phase of a newly introduced cryptocurrency or in the expansionary phase of a speculative bubble, volatility and price reactions differ markedly from those observed in a more mature and regulated phase. This is also reflected in the historical trajectory of Bitcoin's volatility: in its early years, annualised realised volatility frequently exceeded 200–300%, whereas in more recent years – concomitant with rising market capitalisation and the entry of institutional participants – a downward trend in volatility has been observable (Fidelital Digital Assets, 2024).

In this study, we propose a solution to the following research problem:How can the forecasting of cryptocurrency price fluctuations be enhanced in a manner that simultaneously improves predictive accuracy, adaptivity, and transparency? To address this question, we introduce an innovative, multi-layered AI-on-AI architecture – provisionally termed CryptoLife HYDRA-SAI – which adopts a multi-agent approach and integrates several advanced artificial intelligence modules for the prediction of cryptocurrency prices and extreme volatility events. The CryptoLife HYDRA-SAI (Crypto-market Life Cycles Hybrid Dynamic Resilient Analytics Sentinel AI-based) decision-support framework combines the dual-AI principle with a triple-AI approach and incorporates a specialised multi-agent learning network. In addition, we implement lifecycle-based modelling that adapts to market regime shifts and the maturity stages of digital assets. The four technical components of the framework include: (1) a state-of-the-art DL time-series forecasting module (based on LSTM and hybrid **C**onvolutional **N**eural **N**etwork-**L**ong **S**hort-**T**erm **M**emory, CNN–LSTM architectures); (2) an NLP-based sentiment analysis module to assess market sentiment; (3) a synthetic data generation (Fejes & Katits, 2025c) component employing agent-based market simulations to enhance model resilience; and (4) a real-time, AI-driven early-warning system designed to detect anomalous market patterns. Particular emphasis is placed on the principles of e**X**plainable **AI** (XAI) and trustworthy AI to ensure that the model's decisions are transparent and auditable for end-users, including investors, risk managers, and regulators. Our research methodology incorporates both quantitative and qualitative elements; however, the quantitative component constitutes the primary analytical focus.

II. LITERARY BACKGROUND OF THE CRYPTOLIFE HYDRA-SAI DECISION SUPPORT FRAMEWORK

In response to the cluster of problems identified in Chapter 1 and in direct engagement with the stated research question, Figure 1 presents a multi-layered, resilient, and XAI framework designed to address, in an integrated manner, the requirements of predictive accuracy, adaptivity, and transparency within the cryptocurrency market environment.

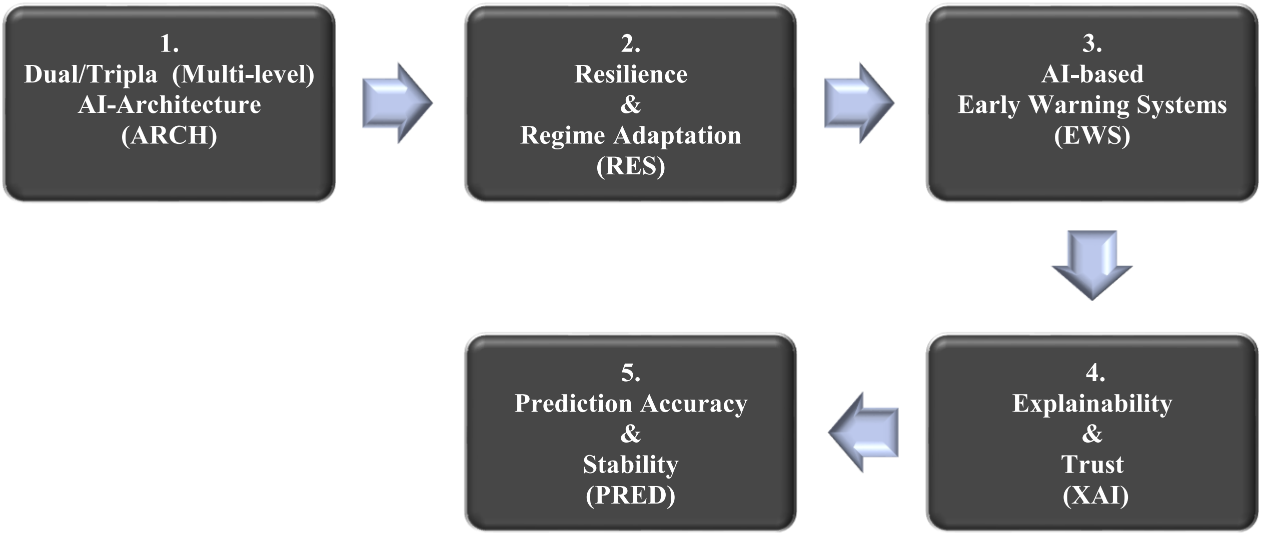

Figure 1. CryptoLife HYDRA-SAI **D**ecision **S**upport (DS) Framework

Source: Author's editing (2026)

The CryptoLife HYDRA-SAI DS framework is based on the coordinated integration of five interrelated scientific and professional modules. Here, we examine how these five components are reflected in the literature (Figure 1.)

1. Dual/Triple AI (Multi-Level) AI (ARCH)

The evolution of artificial intelligence within enterprise decision-support systems may, in our view, be delineated into three principal phases. First, the period of automation-oriented applications, primarily aimed at optimising administrative or logistical processes. Secondly, the proliferation of predictive systems based on ML and DL methodologies, for example in forecasting tourism demand on the basis of seasonal data. Thirdly, the emergence of XAI and transparent AI (TAI), where the transparency of decision-support systems has become particularly salient in sectors such as finance and tourism, in which user trust constitutes a critical success factor.

At present, dual and triple AI architectures seek to operationalise the synergy between predictive capability, explainability, and adaptivity, while also enabling sensitivity to regional or contextual specificities. The deployment of such systems raises novel questions concerning knowledge utilisation: in what ways can ML complement managerial experience, and how might the two jointly reinforce the exchange, structuring, and preservation of organisational knowledge?

Concurrently, the rapid diffusion of Edge AI technologies – that is, the decentralisation of data processing towards the network periphery – creates opportunities for real-time decision support. This enables managers to base their decisions on up-to-date, context-sensitive knowledge, while simultaneously generating infrastructural and governance challenges related to system integration and technological development.

We conceptualise dual AI as a configuration in which automated knowledge processing and human-driven analytical judgement operate in a balanced and mutually reinforcing manner. Its objective is to combine the high-speed processing capacity of AI systems with the interpretative and critical faculties of human decision-makers. The anticipated effect is an increase in organisational efficiency, as human–machine collaboration may yield more accurate and timely decisions.

Triple AI extends this paradigm further. Beyond aligning machine and human intelligence, it incorporates the deliberate training of managers and the systematic integration of soft skills – such as empathy, critical thinking, and ethical sensitivity – into the decision-support ecosystem. In this framework, human factors assume heightened importance alongside technological capabilities, particularly in the context of responsible leadership. The expected outcome is more sustainable knowledge management, supporting not only short-term efficiency gains but also long-term organisational learning and resilience (Figure 2).

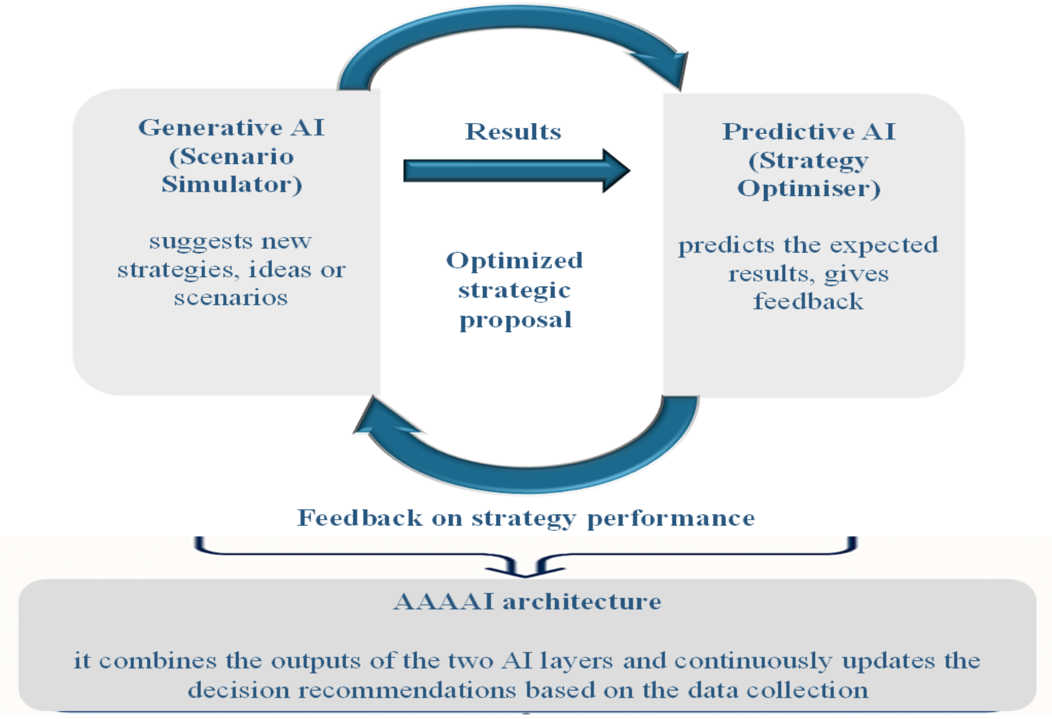

Figure 2. Content and Operational Logic of Dual/Tripla AI

Source: Author's edit (2026)

We define AI-on-AI as a system architecture in which one artificial intelligence model or agent supervises, optimises, or directs the operation of another AI model. In the literature, this paradigm is frequently conceptualised within the frameworks of meta-learning or learning-to-learn, wherein a higher-level model continuously evaluates the performance of lower-level models and performs adaptive interventions (Finn et al., 2017). Such an approach enhances system adaptivity and robustness in non-stationary environments, where data distributions and structural conditions evolve over time.

Multi-layered AI architectures consist of hierarchically organised, cooperating AI modules, in which lower-level predictive models are coordinated by one or more meta-level components. While increasing hierarchical depth may theoretically enhance representational capacity and expressive power, excessive layering may compromise interpretability and trainability, as emphasised in research on hierarchical learning systems (Bengio et al., 2013). Accordingly, architectural design must balance expressive richness with transparency and operational feasibility.

Edge AI refers to technological configurations in which AI algorithms operate directly on local devices – such as smartphones, sensors, or industrial machines – rather than transmitting data to remote cloud-based servers for processing (IBM, 2026). Through data-proximate processing, Edge AI introduces a qualitatively new dimension for end-users. By enabling faster, real-time data analytics, informational latency is reduced, thereby allowing investors to make decisions grounded in up-to-date knowledge. In addressing explainability and transparency challenges associated with Edge AI, approaches rooted in XAI, including SHAP (SHapley Additive exPlanations), provide important methodological guidance (Fejes & Katits, 2025a; Lundberg & Lee, 2017).

2. Resilience and Regime Adaptation (RES)

Resilience requires that systems be capable of adapting to changes in environmental and data conditions, maintaining operational continuity under shock scenarios, and – ideally – doing so in a secure and controlled manner. Within the CryptoLife HYDRA-SAI decision-support framework, resilience is not conceived as a peripheral add-on module but rather as a central mediating mechanism. For decision-makers, the critical objective is not merely the maximisation of average predictive accuracy, but the capacity to adapt effectively to shock-like events and structural regime transitions.

Resilience may be characterised through interrelated dimensions such as adaptation, recovery, performance preservation, absorption, retention, confrontation, response, and resistance (Zahedi et al., 2023). In this context, risk constitutes the threat, whereas resilience represents the structured response to that threat. The international standard ISO 31000 provides a comprehensive framework for risk management – encompassing financial, operational, strategic, IT, cybersecurity, and compliance risks – that can be adapted across organisational contexts. Its core principles include systematic risk identification, assessment, continuous management, and the integration of risk governance at all organisational levels. In accordance with the ISO 31000 approach, AI technologies – including dual-AI-based predictive systems – may play a pivotal role in the continuous risk management cycle (planning, implementation, monitoring, and improvement), particularly in forecasting emerging threats and supporting the automation of risk responses (TechTarget, 2025). In this regard, the RISKRES (Risk–Resilience) model (Singh, 2022) offers an integrative perspective by jointly addressing risk analysis and the development of resilient strategies.

Wei et al. (2025) proposed an LSTM-based predictive framework augmented with an agent-based synthetic data generation system, demonstrating improved forecasting accuracy and stability during episodes of extreme market turbulence. Their findings substantiate the argument that generative approaches constitute an effective method for mitigating data scarcity and enhancing robustness under rare-event conditions. The incorporation of synthetic data (Nikolenko, 2021) also facilitates earlier detection of regime shifts. This effect may be attributed to the meta-agent's exposure, via simulation, to a wider spectrum of extreme patterns, thereby fostering a more precautionary and anticipatory stance even under lower levels of observable uncertainty. Such proactive responsiveness confers a substantial advantage in financial risk management by affording decision-makers additional time for strategic preparation.

By 2026, the cryptocurrency market has transitioned from a predominantly speculative phase to an era characterised by increasing institutional integration and the development of regulated infrastructures. Market resilience is therefore no longer defined primarily by abrupt price surges, but rather by deeper interconnections with traditional financial systems and the deployment of increasingly sophisticated risk management instruments.

In the first quarter of 2026, four structural drivers of resilience and adaptive capacity can be identified within the cryptocurrency market environment.

(1) Regulatory stability and iInstitutional trust. We observe that the principal source of market resilience in 2026 lies in regulatory clarity. Whereas legal uncertainty had previously constrained capital inflows, the full European implementation of MiCAR and the entry into force of the U.S. GENIUS Act (**G**uiding and **E**stablishing **N**ational **I**nnovation for **U.S.** Stablecoins Act) have effectively erected regulatory "guardrails" around the market (Amina Group, 2026). This development has enabled digital assets to become a standard component of diversified investment portfolios (BPM, 2025), thereby reinforcing institutional confidence and structural stability.

(2) Tokenisation of real-world assets. Adaptive capacity has been significantly strengthened by the expansion of tokenised government bonds and real estate instruments, which by 2026 have evolved from an experimental phase into a tangible economic force (BDO USA, 2026; Chainstack, 2026). By early 2026, the market for tokenised assets had surpassed USD 25 billion in volume, contributing to the stabilisation of the decentralised finance (DeFi) ecosystem (Li, 2026).

(3) Macroeconomic eesilience. **T**he market correction of January 2026 demonstrated that cryptocurrency markets increasingly respond not to endogenous speculative shocks, but to global macroeconomic developments. This behavioural shift signals a maturing integration with the traditional financial system (Amina Group, 2026).

(4) Technological and infrastructural maturity. **By** 2026, institutional investors no longer seek mere Bitcoin exposure; rather, they employ multi-party computation custody solutions and basket-based structured products to diversify and manage risk (Silenskyte, 2026).

Overall, Q1 2026 is characterised by the duality of technological maturity and institutional integration. While structural foundations have strengthened, novel operational and macroeconomic risks pose substantial challenges to market participants.

Three key Risks in Q1 2026:

(1) Operational and security vulnerabilities. Despite infrastructural maturation, January 2026 recorded theft-related losses exceeding USD 370 million. Notably, the locus of vulnerability has shifted from smart-contract deficiencies towards human-centred weaknesses, including AI-generated voice spoofing and phishing attacks (Vecchietti et al., 2025).

(2) Macroeconomic and geopolitical shocks. During Q1 2026, crypto-assets exhibited strong correlations with sovereign risk indicators and monetary regime shifts. Geopolitical tensions and rising energy prices exerted direct negative effects on investor risk appetite (Al-Harbi, 2026).

(3) Residual regulatory uncertainty. Although regulatory progress has been substantial, uncertainties remain regarding the precise timing and final form of U.S. market-structure legislation (e.g. the CLARITY Act), potentially delaying the full realisation of market potential (K&L Gates, 2026)

3. AI-Based Early Warning Systems

According to Katits (2024), corporate **E**arly **W**arning **S**ystems (EWS) have evolved through four distinct generations.

First Generation **-** Rule-based and threshold models, such as the Altman Z-score (Altman, 1968), focused primarily on signalling early financial distress.

Second and Third Generations **–** These systems relied on larger datasets and predominantly statistical techniques under static assumptions (Beaver, 1966; Jones et al., 2011). While offering earlier recognition of financial deterioration or growth opportunities, they remained constrained by linear modelling frameworks.

Fourth Generation **–** Contemporary AI-driven systems integrate ML, Big Data analytics, and Natural Language Processing (NLP) to process heterogeneous, real-time data streams (Theodorakopoulos et al., 2024; Malali, 2025). These systems uncover non-linear patterns and latent risk factors (Altman et al., 2018; Nordmann et al., 2025 simulation studies), thereby markedly enhancing predictive capability.

Historically, the first generation of EWS emerged in the 1960s from bankruptcy prediction models, representing a significant step forward in anticipating corporate failure, albeit with limited capacity to address complex financial environments. The 1980s saw the advent of software-based EWS, enabled by advances in computing technology, allowing the application of larger datasets and more sophisticated statistical models. Nonetheless, these systems remained heavily reliant on historical data and linear forecasting techniques.

From the 2000s onwards, the incorporation of AI facilitated the analysis of real-time data streams, a crucial development in rapidly evolving economic contexts. Presently, hybrid EWS configurations prevail, integrating AI, Big Data, and multivariate statistical methodologies. The economic disruptions triggered by the COVID-19 pandemic underscored the necessity of robust EWS capable of detecting both latent and fully developed crises, thereby supporting preventive and proactive management (Tanaka et al., 2025).

In generational terms, first-generation systems fulfil the classical early warning function (e.g. signalling operational losses or liquidity risks). Second-generation systems provide early recognition, identifying potential growth paths contingent upon managerial intervention. Third- and fourth-generation systems perform early detection and forecasting, frequently offering structured intervention programmes with detailed implementation pathways. There is thus a clear demand for EWS solutions capable of identifying financial and operational risks – as well as opportunities – aligned with firms' developmental stages, thereby enhancing organisational resilience and facilitating crisis prevention.

Within dual-AI architectures, one AI agent may continuously monitor data streams and predict emerging threats (for example, regulatory or climate-related risk indicators), while a second AI model conducts strategic simulations – such as Monte Carlo analyses or agent-based modelling – to evaluate alternative response strategies (Fejes & Katits, 2025b).

In triple-AI (Adaptive–Active–Augmented) EWS configurations, three integrated yet functionally distinct components operate in concert: (1) predictive crisis forecasting, (2) simulation-based decision modelling, and (3) automatically generated – yet human-supervised – turnaround strategies. In such hybrid systems, explainability and human oversight assume central importance (Dai & Vasarhelyi, 2023).

Through these layered AI structures, responses to risk become faster, more adaptive, and more comprehensive, thereby materially strengthening corporate resilience in increasingly complex and non-stationary environments.

4. Explainability & Trust (XAI)

High predictive accuracy, in itself, is insufficient. User trust can only be established where the decisions of an AI system are transparent, comprehensible, and accompanied by explanations that are meaningful and contextually relevant to stakeholders (Pal et al., 2024). In this respect, we conceptualise XAI not as a merely technical add-on, but as an institutional mechanism of legitimacy.

The primary objective of XAI is to render the decision-making processes of complex DL models – such as LSTM or hybrid CNN–LSTM architectures – interpretable and transparent. This is indispensable both for institutional trust and for regulatory compliance, particularly under emerging frameworks such as the EU AI Act. Predictive accuracy alone does not suffice; investors and risk managers must understand why a model forecasts a price decline or appreciation. XAI techniques, including SHAP (**SH**apley **A**dditive ex**P**lanations) and LIME (**L**ocal **I**nterpretable **M**odel-agnostic **E**xplanations), enable systematic mapping of internal model logic and feature contributions.

Nastoska et al. (2025) argue that trustworthiness cannot be captured by a single scalar metric but must instead be assessed through a multidimensional evaluative process. They propose quantitative indicators for fairness, explainability, and data protection, demonstrating that achieving trustworthiness requires explicit trade-offs among competing metrics – for example, fairness versus efficiency, or privacy versus transparency. Their findings underscore the necessity of interdisciplinary integration in the design and governance of AI systems.

Giudici et al. (2024), in their historical validation analysis, demonstrate that the most influential factors identified by predictive models typically include lagged price levels and historical volatility – a theoretically coherent outcome, given the well-established predictive strength of technical trends. However, external variables also recurrently appear among the leading determinants, including large sell-side volumes, the frequency of negative news, and stock market volatility indices. These findings confirm that an integrated modelling approach prevails: no single data source dominates across all contexts; rather, factor importance varies with market conditions, consistent with established financial analytical intuition.

In our view, XAI constitutes a foundational pillar of systemic stability. By enhancing interpretability, it contributes to the prevention of model-induced market anomalies and potential "flash crashes" triggered by opaque algorithmic behavior. At the same time, XAI has a decision support function and a risk management/governance element. It can be adapted to accepted institutional frameworks. We conceptualise explainability as building trust across three interrelated levels:

(1) Feature Importance. This level reveals whether the model assigns the greatest weight to price dynamics, social media sentiment, or large “whale” transactions

(2) Local Explanations. For a specific market event (e.g. a sudden 5% price decline), local interpretability methods clarify the causal drivers of the individual forecast. Explainability in financial forecasting is categorized into global interpretability, which ranks overall drivers like market sentiment, and local interpretability, which justifies specific model outputs during high-volatility events (Arrieta et al., 2020)

(3) Model Debugging. Explainability facilitates the detection of spurious correlations (e.g. coincidental time-of-day effects), thereby mitigating the risk of catastrophic capital losses. By employing XAI for model debugging, financial institutions can identify and prune spurious correlations that do not align with economic fundamentals, thereby preventing catastrophic losses in automated trading (Linardatos et al., 2020). Bücker et al. (2022) XAI-driven sensitivity analysis serves as an advanced anomaly detection tool, flagging instances where a model over-relies on a single technical indicator, which ensures systemic stability in volatile markets.

5. Prediction Accuracy & Stability (PRED)

Robust predictive frameworks require representative and generalisable performance measurement, alongside continuous monitoring of stability. Accuracy refers to the proportion of correct predictions, whereas robustness and stability denote the model's capacity to sustain performance under novel or shifting conditions.

Recent DL architectures (e.g. LSTM, GRU, hybrid CNN models) have achieved directional accuracy rates of approximately 80–96% in predicting upward or downward price movements. However, precise point-level price estimation remains constrained by intrinsic market noise. Hang and Thuy (2024) emphasise that the highest predictive performance is not achieved by standalone models but by hybrid configurations. For instance, a CNN–LSTM architecture – wherein the Convolutional Neural Network extracts salient technical features and the LSTM captures temporal dependencies – produces significantly more stable forecasts than either model applied independently.

Joebges et al. (2025) elaborate on the risks associated with the difficulty of setting up regulatory institutions in the crypto sphere and the likelihood of periods of high volatility as well as their repercussions on the traditional financial system due to reciprocal integration. Griffin & Shams (2020) critically analyze the market-influencing and liquidity-providing role of stablecoins (especially Tether) in market stress situations. Bouteska et al. (2024) demonstrate that ensemble approaches outperform single-model configurations. Building upon this insight, we introduce a time-varying ensemble rule within the CryptoLife HYDRA-SAI framework. By dynamically adjusting model weights in response to regime shifts, the system eserves predictive advantage during volatility shocks, whereas fixed-weight ensemble structures exhibit marked performance deterioration under turbulent conditions.

For financial decision-makers, therefore, model value is not determined solely by predictive accuracy, but equally by interpretability, auditability, and resilience under stress scenarios.

Overall, we prefer hybrid solutions because the crypto market produces two different types of data:

1. Spatial/Structural patterns: The relationships between technical indicators (RSI, MACD, Volume), which are captured by CNN layers.

2. Temporal dependencies: The sequence of prices, which are handled by LSTM gates (volatile, input, output).

1.1. Theoretical Trends Related to the CryptoLife HYDRA-SAI Decision-Support Framework

Our research is situated at the intersection of several interrelated theoretical streams. These frameworks not only provide the methodological foundation for the proposed architecture but also create an opportunity for the empirical findings of the study to contribute meaningfully to ongoing theoretical debates (Figure 3).

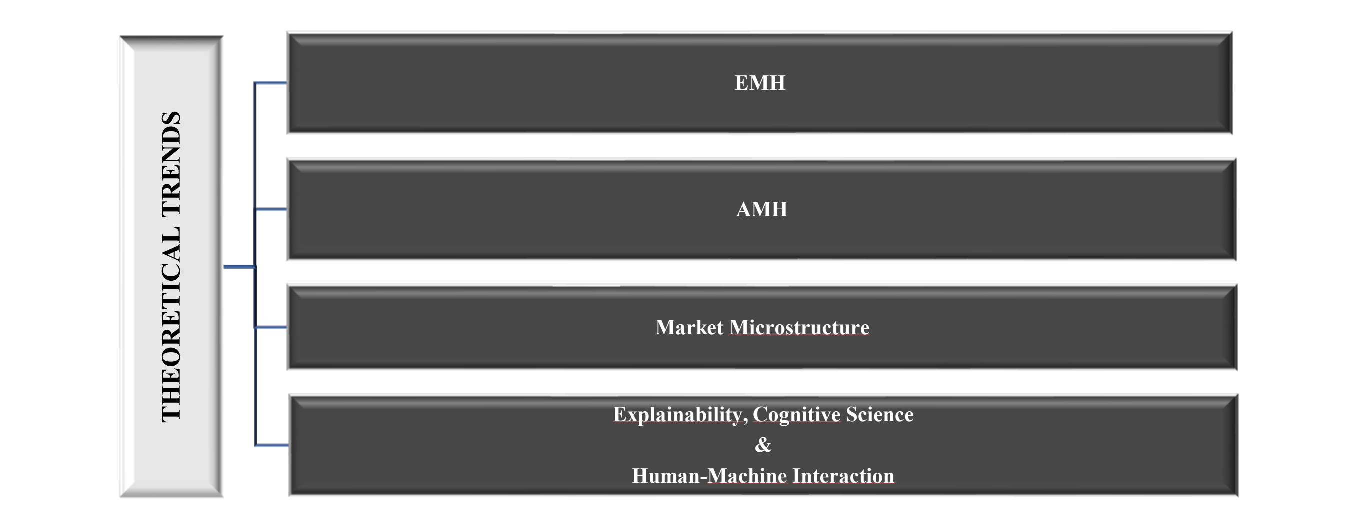

Figure 3. Theoretical Trends of the CryptoLife HYDRA-SAI DS Framework

Source: Author's edit (2026)

The EMH posits that asset prices instantaneously reflect all publicly available information; consequently, markets cannot be systematically outperformed in the long term (Fama, 1970). In the context of crypto-assets, however, a growing body of academic studies and supervisory reports suggests that markets remain fragmented, information flows are asymmetric, and pronounced behavioural biases are observable. These characteristics indicate that classical notions of efficiency hold only to a limited extent in cryptocurrency markets (BIS, 2024).

Our research engages with the EMH in the following manner: if the CryptoLife HYDRA-AIDSS framework proves capable of forecasting extreme price movements and volatility breakouts, this would constitute empirical evidence that, at least in the short term or under transitional conditions, predictable patterns exist in crypto-markets. Such findings would be consistent with behavioural finance literature documenting overreactions, underreactions, and irrational investor behaviour, particularly in environments characterised by elevated uncertainty (BIS, 2024). The indicators identified within the CryptoLife HYDRA-AIDSS framework – such as extreme sentiment metrics or order book imbalances – may capture informational signals that remain inaccessible, or only partially accessible, to traditional modelling approaches.

The second major theoretical pillar of the study is the **A**daptive **M**arket **H**ypothesis (AMH), which conceptualises financial markets as evolutionary systems in which participants' strategies continuously adapt to environmental changes (Lo, 2004). According to the AMH, market efficiency is not a static condition but a time-varying property. Within the CryptoLife HYDRA-AIDSS framework, this theoretical perspective is operationalised algorithmically through a meta-learning component. The essence of meta-learning lies in enabling the model not merely to learn from data, but to optimise the learning process itself – for example, through the dynamic adjustment of hyperparameters or structural configurations. The system continuously monitors forecasting errors and statistical drift; in the presence of persistent deviations, it initiates adaptive retraining. This operational logic aligns directly with the Adaptive Market Hypothesis and renders it empirically testable within a quantitative framework.

The theoretical foundation of the multi-agent approach derives from market microstructure theory, which describes markets as the outcome of interactions among heterogeneous agents – including informed traders, noise traders, and liquidity providers (O'Hara, 1998). The agent-based simulations employed in this research allow these interactions to be modelled explicitly, thereby creating an experimental environment for investigating the mechanisms underlying volatility formation and bubble dynamics. Strategic interactions among agents may also be interpreted within a game-theoretic framework, particularly as an increasing number of market participants deploy AI-driven trading systems. The adoption of multi-agent architectures is consistent with recent AI-based financial market models that emphasise the analytical perspective of **C**omplex **A**daptive **S**ystems (CAS) (Hong et al., 2025).

The acceptance of AI-based financial systems is critically contingent upon XAI. Insights from cognitive science and human–machine interaction theory indicate that user trust depends substantially on the ability to construct a coherent mental model of algorithmic functioning (Miller, 2019). Accordingly, explanations must be contextual, accessible, and, where feasible, counterfactual in nature. The explanatory module developed in this research adheres to these principles and is aligned with professional guidance within the financial sector. The CFA Institute (2025) emphasises that explainability in financial AI systems is not uniform but must be tailored to the needs of different stakeholders – including investors, risk managers, and supervisory authorities. A key practical contribution of this study is the presentation of an XAI solution that operationalises this theoretical requirement within a concrete financial application.

In sum, the research is situated at the intersection of financial economics, artificial intelligence, behavioural science, and systems theory. This interdisciplinary positioning enables the study to contribute simultaneously to the theoretical understanding of crypto-markets and to the development of practical risk management solutions. The resulting theoretical framework provides a robust analytical lens for interpreting empirical findings and guiding future research trajectories.

The subsequent two chapters present the research materials and methodology, detailing how the above theoretical principles have been implemented in practice.

III. RESEARCH MATERIAL AND SAMPLING PROCESS

The research material comes from two sources:

1. Long time series from reliable sources are needed for temporal validation. The daily closing price and market capitalization data from the CoinMarketCap API cover the period from January 1, 2019 to January 31 (1 857 days, both cutoff dates are included), 2025 for Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC) (CoinMarketCap, 2026). At hourly resolution, each day provides 24 observations, so the length of the time series is: 1,857×24=44,568 hours. For the out-of-sample (later) analysis, we separate the period from February 1, 2024 to January 31, 2025, which contains 366 days (2024 is a leap year), so a test sample of 8,784 hours provides the backtest.

2. Survey research among the target expert community engaged in cryptocurrency market forecasting, AI, and financial analytics.

The study does not aim at demographic representativeness of the general population; rather, it seeks structural representativeness of the expert population relevant to AI-based cryptocurrency forecasting and financial decision-support.

Accordingly, the representativeness of the research sample pertains not to the entire population but to the target expert community engaged in cryptocurrency market forecasting, artificial intelligence, and financial analytics. Within this defined population, the sample demonstrates structural representativeness across dimensions of professional background, age distribution, and gender composition, in alignment with Eurostat and international AI labour market statistics.

Geographically, the distribution is intentionally Hungary–EU focused, supplemented by global respondents, reflecting the European regulatory and market embeddedness of the CryptoLife HYDRA-SAI decision-support framework. In the experiential dimension, in the absence of an official benchmark, we applied an expert sampling logic, an accepted methodological approach in innovation- and technology-oriented research domains.

Thus, the sample may be regarded as empirically and theoretically justified as representative of the defined target population and is suitable for drawing conclusions based on quantitative analysis.

Table 1 compares Hungary-EU-global reference values with the characteristics of the research sample and presents the interpretation of deviations in a reviewer-friendly manner.

Table 1. Hungary-EU-global Benchmarks Depending on the Research Sample with an Assessment of Representativeness

Dimension	Research Sample (N≈2000)	Hungary (reference)	EU (reference)	Global (reference)	Interpretation of Representativeness

Professional Background	researchers, financial analysts, fintech/AI developers, regulatory experts	ICT+financial sector dominance	ICT sector ~60.6%, finance+professional ~16% (Eurostat, 2024)	technology and financial sector dominance (BIS, 2023)	☑ structurally fits the target population
Crypto/AI Experience	most have medium to high experience	no official breakdown	no official breakdown	no official breakdown (OECD, 2025)	☑ reasoned expert sampling in innovation-driven research
Geographic Distribution	Hungary+EU overweight, global respondents	EU, HU ICT ratio low but relevant	German, French, Spanish dominance in ICT employment (Eurostat, 2024)	USA, EU, East Asia	☑ targeted, theoretically justified, regulatory and market-focused relevant coverage
Age	Majority 30-55 years old	most ICT professionals are middle-aged	ICT professionals: 35–74 years = 62.8% (Eurostat, 2024)	middle-aged dominance in the tech sector (OECD, 2025)	☑ consistent with the ICT/AI expert profile
Gender	male dominance (~75–80%)	ICT: ~85% male (Eurostat, 2024)	ICT: ~80,5% male (Eurostat, 2024)	AI experts: ~78% male (OECD, 2025)	☑ reflects the structural characteristics of the sector
Sample Size	1986-2121 people	–	–	–	☑ CFA and SEM are methodologically excellent
Sampling Logic	targeted expert sample	–	–	–	☑ suitable for innovation-driven research

Source: Author's compilation (2026)

Table 1 compares official reference values for Hungary, the European Union, and the global level with the characteristics of the research sample, in order to demonstrate that the empirical data collection is structurally representative of the defined target population. Representativeness is interpreted not with respect to the general population, but in relation to the expert community engaged in cryptocurrency market forecasting, artificial intelligence, and financial decision-support, in accordance with established practice in technology- and innovation-oriented research.

With regard to professional background, the composition of the research sample – comprising researchers, financial analysts, fintech and AI developers, and regulatory experts – corresponds closely to the structural profile of the European and global ICT and financial expert workforce. According to Eurostat data, more than 60% of ICT specialists in the European Union are employed within the information and communication technology sector, while a further approximately 16% operate in financial, insurance, and professional-scientific services (Eurostat, 202a). These sectors directly overlap with the expert groups targeted by the CryptoLife HYDRA-SAI decision-support framework; thus, the professional composition of the sample exhibits structural alignment with the relevant target population.

In the dimension of crypto- and AI-market experience, no official aggregated statistics are currently available – neither in Hungary nor at EU or global levels – that uniformly measure the experiential depth of such experts. This gap is acknowledged in the literature, as official statistical offices typically capture general digital skills and ICT employment rather than specific crypto- or AI-market expertise (OECD, 2025; World Bank, 2025). Accordingly, we applied targeted expert sampling, an accepted methodological approach in innovation-driven and technology-focused research domains where relevance is primarily defined by professional competence.

Concerning geographical distribution, the sample is intentionally Hungary–EU focused, complemented by global respondents. This design reflects the fact that the European Union constitutes one of the largest concentrations of ICT and fintech professionals worldwide, with the number of ICT specialists exceeding nine million and concentrated particularly in major Member States such as Germany, France, and Spain (Eurostat, 2024). Although Hungary represents a smaller proportion within the EU aggregate, it remains relevant in regulatory and market terms as part of the EU Digital Single Market. Globally, the majority of technology and financial experts continue to be concentrated in North America, Europe, and East Asia, as corroborated by international financial and labour statistics (BIS, 2023; World Bank, 2025).

The age distribution further supports structural representativeness. Eurostat reports that approximately 62.8% of ICT specialists in the EU belong to the 35–74 age cohort, while 37.2% fall within the 15–34 age group (Eurostat, 2024). This indicates that the ICT and AI expert population is predominantly composed of mid-career and senior professionals, consistent with the 30–55 age dominance observed in the research sample.

Regarding gender composition, the male predominance observed in the sample reflects sectoral realities rather than sampling bias. According to Eurostat, only around 19.5% of ICT specialists in the EU are women, while in Hungary the proportion is approximately 15% (Eurostat, 2024a). In certain contexts, the imbalance is even more pronounced: in Hungary in 2024, 84.8% of ICT specialists were male, implying that women accounted for only about 15.2%. At the global level, a 2024 international survey indicates that women represent approximately 22% of AI professionals (Pal et al., 2024). Taken together, these statistics suggest that a sample of crypto- and AI-experts will, by structural necessity, display male dominance; in order to achieve gender representativeness, the proportion of female respondents should approximate the empirically observed 20–22% range within the ICT/AI workforce (Eurostat, 2024; OECD, 2025; Pal et al., 2024).

The sample size (N=1986–2121) exceeds international methodological recommendations for both **C**onfirmatory **F**actor **A**nalysis (CFA) and **S**tructural **E**quation **M**odelling (SEM), and is therefore statistically adequate for the estimation of complex, multi-construct models (Hair et al., 2022).

In summary, the research sample does not aim to represent the general population in demographic terms; rather, it achieves structural and functional representativeness with respect to the expert population relevant to AI-based cryptocurrency forecasting. Across the dimensions of professional background, age distribution, and gender composition, the sample aligns with official European and global ICT and AI workforce statistics (Eurostat, 2024; OECD, 2025). The geographical focus on Hungary and the European Union corresponds to the regulatory and market embeddedness of the CryptoLife HYDRA-SAI decision-support framework.

IV. RESEARCH METHODOLOGY

One part of the present research is the examination of the prices of three selected crypto assets - The long-term trend of the prices is illustrated by the relative growth rates (r). The relative growth can be calculated as the ratio of the starting (P_0) and the closing (P_T) value:

$$r = \frac{P_T}{P_0} \qquad (1)$$

where growth %=$(r-1) \times 100$

Cryptocurrency time series contain strong heteroscedasticity and outliers. The calculation of the logarithmic return (r_t) reduces the variance and approximates the normal distribution:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (2)$$

where P_t is the exchange rate at time *t*.

This is followed by min–max normalization, which scales the series to the interval [0,1]:

$$\tilde{r}_t = \frac{r_t - \min(r)}{\max(r) - \min(r)} \qquad (3)$$

During preprocessing, it is worth removing outliers (e.g. deviations greater than 3 standard deviations) and checking stationarity with the **K**wiatkowski–**P**hillips–**S**chmidt–**S**hin **(**KPSS) or **A**ugmented **D**ickey–**F**uller (ADF) test. If necessary, differentiation can be used to ensure stationarity, which is a prerequisite for classic ARIMA models.

Time series predictive models should be divided by time to avoid data leakage. In the project under study, we used data from 2019–2024 as the training set, while we kept 366 days from February 1, 2024 to January 31, 2025 as the out-of-sample test data set. To fine-tune the model parameters, we applied rolling window cross-validation on the training set: we slid a window of a given length (e.g. 730 days) of the training time series over the entire period, with a new model training and validation in each window. Alternatively, an expanding window strategy can be used, where the window is continuously expanded; this tests the stability of adaptive models (Cocco et al., 2021).

The purpose of out-of-sample backtesting is to assess how well the model generalizes to new, previously unseen data. The sample (2024. 02. 01. – 2025. 01. 31.) contains 366 days (8,784 hours). We evaluate the model performance using several error measures:

Mean Absolute Error MAE=$\frac{1}{N}\sum_{t=1}^{N}|\hat{y}_t - y_t|$ (4)

Root **M**ean **S**quare **E**rror RMSE=$\sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{y}_t - y_t)^2}$ (5)

Marginal **A**bsolute **E**rror MAPE= $\frac{100}{N}\sum_{t=1}^{N}\left|\frac{\hat{y}_t - y_t}{y_t}\right|$ (6)

Directional **A**ccuracy (DA) the proportion of correct predictions of modeled direction changes.

The comparison of time series prediction models was conducted based on Shahbazi & Byun (2022) *Sensors* article. In it, the XGBoost algorithm is compared with CNN, ARIMA, Multilayer Perceptron and LSTM models based on MAE, RMSE, MAPE values. The article emphasizes that the LSTM and XGBoost algorithms provide the best performance, but XGBoost has lower computational requirements.

Another part of the present research was the open-ended question (Q24) included in the questionnaire, which invited respondents to articulate, in their own words, the most critical determinants of practical success for AI-based cryptocurrency decision-support systems. This approach enabled us to uncover implicit interpretations, emphases, and narrative structures that cannot be fully captured through quantitative Likert-type scales.

Qualitative data were analysed using an inductive thematic content analysis, implemented through a three-stage coding procedure. The objective of the analysis was not hypothesis testing, but rather the empirical identification of meaning patterns emerging from the responses, followed by their systematic linkage to relevant theoretical constructs.

In the first stage, open coding was conducted by analysing textual responses line by line, identifying recurring key concepts such as “explainable decisions”, “recognition of regime shifts”, “reliability of early warning”, and “human oversight and auditability”. The purpose of this phase was to capture substantive content units without imposing prior theoretical assumptions.

During axial coding, open codes were organised into more structured categories, and their relationships to the latent constructs of the quantitative research model were explored. For example, the codes “explainable decisions” and “auditability” were linked to the construct of explainability (XAI), whereas “regime shift recognition” and “adaptive retraining” were associated with the dimensions of resilience and multi-level AI architecture.

In the selective coding phase, dominant and theoretically salient core themes were identified and integrated from the axial categories. The analysis yielded four principal qualitative themes: (1) Explainability and Trust; (2) Regime Shift Management and Adaptivity; (3) Timing and Reliability of Early Warning; and (4) The Role of Human-AI Collaboration.

Exploratory **F**actor **A**nalysis (EFA) was employed to identify the latent structure underlying the quantitative dataset. The primary objective of EFA is to reduce observed questionnaire items into a smaller number of unobserved background variables, or factors, thereby determining the dimensional structure of the data. In our study, EFA was conducted to examine the extent to which the empirical factor structure supports the conceptual architecture of the CryptoLife HYDRA-SAI decision-support framework (Figure 1). Factor interpretation followed the clean-loading principle: an item was assigned to a factor if its loading on that factor was high while remaining comparatively low on other factors. The relationship between the *j*-th observed variable and the *k*-th latent factor is expressed through the factor loading:

$$\lambda_{jk} = corr\left(x_j, F_k\right) \qquad (7)$$

where λ_{jk} denotes the loading of the *j*-th variable on the *k*-th factor;; x_j represents the *j*-th observed variable; F_k denotes the *k*-th common factor.

The EFA procedure involved several steps. First, sampling adequacy and the correlation structure among variables were assessed. Second, the number of factors was determined using eigenvalues (Kaiser criterion). Third, factor rotation was applied (Varimax for orthogonal rotation or Oblimin for oblique rotation) to enhance interpretability. Finally, factors were labelled on the basis of the substantive content of their associated variables.

Building upon the EFA results and the pre-defined theoretical model, we conducted CFA to validate the measurement model. The purpose of CFA was not to discover new structures, but to empirically confirm theoretically specified constructs. The measurement model was specified reflectively, whereby individual items are conceptualised as manifestations of underlying latent variables. In general form, the CFA model may be expressed as: $\mathrm{x} = \Lambda_x \xi + \delta$, where x denotes the vector of observed indicators; ξ represents the vector of latent constructs; Λ_x is the matrix of standardised factor loadings; ε denotes the vector of measurement errors.

Through this sequential integration of qualitative thematic analysis, exploratory factor analysis, and confirmatory factor modelling, we sought to ensure both conceptual depth and statistical rigour in validating the multidimensional architecture of the CryptoLife HYDRA-SAI decision-support framework.

Convergent validity was assessed on the basis of three key indicators.

1. Standardised factor loadings**,** which express the strength of the relationship between an observed indicator and its corresponding latent construct. Their values typically range between −1 and +1, with higher absolute values indicating a stronger association between the item and the underlying factor.

$$\lambda_i = corr(x_i, \xi_i) \qquad (8)$$

Equation (2) holds under the condition that an orthogonal (Varimax) rotation is applied.

2. **C**omposite **R**eliability (CR) is calculated using the standardised factor loadings (λ) obtained from the CFA and the corresponding measurement errors (ε). It provides an estimate of the internal consistency of the latent construct and is computed as:

$$CR = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \sum_{i=1}^{n} \varepsilon_i} \qquad (9)$$

where $\lambda_i$denotes the standardised factor loading of the i-th indicator; ε_i represents the associated measurement error variance; n denotes the number of items belonging to a given latent variable.

A CR value exceeding 0.70 is generally considered indicative of satisfactory internal consistency in SEM contexts.

3. **A**verage **E**xtracted **V**ariance (AVE), which is calculated on the basis of the standardised factor loadings ((λ) according to Equation (10):

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n} \qquad (10)$$

The AVE reflects the proportion of variance captured by the latent construct relative to the variance attributable to measurement error. An AVE value of 0.50 or higher is generally considered indicative of adequate convergent validity, as it implies that the construct explains at least half of the variance of its indicators.

Discriminant validity was examined using two complementary methods.

1. According to the Fornell-Larcker approach, a latent variable (factor) must exhibit a stronger relationship with its own indicators than with any other latent construct included in the model. Discriminant validity of a construct is established if the square root of its AVE exceeds its correlations with all other latent constructs in the model. Formally, this condition is satisfied when

$$\sqrt{AVE_k} > r_{kj} \forall j \neq k \qquad (11)$$

where AVE_k denotes the AVE of the k-th latent construct; r_{kj} represents the correlation between the k-th and j-th latent constructs. This criterion ensures that each construct shares more variance with its own indicators than with other constructs, thereby supporting discriminant validity within the measurement model.

2. The **Het**erotrait–**M**ono**t**rait ratio of correlations (HTMT) is defined as the ratio between the mean of the correlations across different constructs (heterotrait–heteromethod correlations) and the mean of the correlations within the same construct (monotrait–heteromethod correlations). It may be expressed formally as follows:

$$HTMT_{ab} = \frac{average\ heterotrait\ correlation}{average\ monotrait\ correlation} \qquad (12)$$

The global fit of the CFA model was evaluated on the basis of four widely accepted goodness-of-fit indices: the **C**omparative **F**it **I**ndex (CFI), the **T**ucker–**L**ewis **I**ndex (TLI), the **R**oot **M**ean **S**quare **E**rror of **A**pproximation (RMSEA); the **S**tandardized **R**oot **M**ean **S**quare **R**esidual (SRMSR). The adequacy of model fit was assessed against the following formal criteria: $CFI, TLI \geq 0.90; RMSEA \leq 0.06; SRMR \leq 0.08$.

Provided that convergent validity, discriminant validity, and global fit indices demonstrate satisfactory values, the subsequent stage of the research proceeds to SEM on statistically sound and unbiased measurement foundations. To test the structural relationships, we employ a **P**artial **L**east **S**quares **S**tructural **E**quation **M**odelling (PLS-SEM) approach. PLS-SEM is particularly well suited to the analysis of complex models with a predictive orientation. The selection of this methodological framework is jointly justified by five considerations: (1) the structural complexity of the model, encompassing multiple endogenous constructs and mediation mechanisms; (2) the dual predictive and explanatory objectives of the research, extending beyond mere covariance-based model fit; (3) the innovative and theory-driven character of the proposed framework (AI-on-AI, multi-level AI architecture); (4) the use of Likert-scale, perceptual indicators; (5) the large sample size (N≈2000), which enables stable bootstrap estimation. In SEM, a **M**ediator (M) is a variable through which the e**X**ogenous variable (X) affects the endogenous variable (Y). The magnitude of the indirect effect can be given by the product of the X→M and M→Y paths (Gunzler et a., 2013). The significance of the mediation is tested using the bootstrap procedure: if the 95% confidence interval of the indirect effect does not contain zero, then the mediation is significant. The structural model comprises five reflective mediator latent constructs: ARCH, RES, EWS, XAI, and PRED (Figure 1). Accordingly, the model examines the directed hypothetical relationships specified in Equations (13)-(16).

RES=β_1 ARCH + ε_1 (13)

EWS=β_2 ARCH + ε_2 (14)

XAI=β_3 ARCH + β_4 RES + ε_3 (15)

PRED=β_5 RES + β_6 EWS + β_7 XAI + ε_4 (16) where β_i is the Standardized Path Coefficient; ε_i is the Error Term.

The explanatory power of the model is assessed using the coefficients of determination (R^2) of the endogenous constructs, according to (17).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \qquad (17)$$

The relative contribution of individual structural paths is assessed using Cohen's effect size (f^2) according to (12).

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}} \qquad (18)$$

where R^2_{included} the explanatory power of the model with the independent variable included; R^2_{excluded} the explanatory power of the model when the investigated independent variable is excluded; $1 - R^2_{\text{included}}$ the proportion of unexplained variance.

The out-of-sample predictive capability of the model was assessed using the Stone–Geisser (Q^2) statistic, computed via a blindfolding procedure as follows:

$$Q^2 = 1 - \frac{\sum(y_i - \hat{y}_{i,\,blind})^2}{\sum(y_i - \bar{y})^2} \qquad (19)$$

where y_i denotes the observed (actual) value; $\hat{y}_{i,\,blind}$ represents the model-estimated value obtained through the blindfolding procedure (i.e. when the given data point was omitted from the estimation process); $\bar{y}$ is the mean of the observed values; the numerator corresponds to the **S**um of **S**quared **P**rediction **E**rrors (SSPE); the denominator represents the **T**otal **S**um of **S**quares (TSS). A positive Q^2 value indicates that the model possesses predictive relevance for the endogenous construct under consideration.

The application of factor analysis and SEM within the quantitative research design ensures both the statistical rigour and the practical relevance of the proposed CryptoLife HYDRA-SAI decision-support framework.

Common **M**ethod **B**ias (CMB) can arise in both qualitative and quantitative research, when the same data collection method (e.g., a questionnaire) artificially intensifies the relationships between variables. We used two approaches in our study:

1. Procedural controls: we shuffled the order of the questions in the questionnaire and ensured the anonymity of the respondents to reduce the impact of social expectations.

2. Statistical test: we calculated the **F**ull **C**ollinearity **V**ariance **I**nflation **F**actor (FCVIF) for each construct. According to the literature, an FCVIF value of <3.3 indicates that there is no significant CMB (Low et al., 2023).

V. RESULTS

For the time validation, we first examined the price development of the three crypto assets. According to Table 2, Bitcoin's price has increased elevenfold (~1,008%) in 5 years, Ethereum's more than sixteenfold (~1,521%), while Litecoin's has only doubled

(~109%). The capitalization ratios are similar: ETH has increased more than eighteenfold, BTC has increased more than twelvefold, while LTC has increased 2.6fold. This suggests that the entire period under review has shown a strong bull regime. However, to examine the stability of a model, it is worth isolating bear regimes (e.g. the crash experienced in Q2 2022), so that different market phases can be included in the cross-validation using a rolling or expanding window method.

Table 2. Basic Parameters of the Three Cryptocurrensy Between 2019 and 2024 - Benchmark

Crypto-currency	Starting Price (01. 01. 2019)	Closing Price (31. 01. 2024)	Price Ratio (r)	Growth (%)	Startin Capitalization (M USD)	Closing Capitalization (M USD)	Capitalization Ratio
Bitcoin (BTC)	3 843,52 USD	42 582,61 USD	11.08	1 007.90	67 098 ,6	835 246,6	12.45
Ethereum (ETH)	140,82 USD	2 282,54 USD	16.21	1 520.90	14 665,3	274 322,0	18.71
Litecoin (LTC)	31,98 USD	66,75 USD	2.09	108.70	1 913,4	4 950,2	2.59

Source: Author's Compilation based on CoinMarketCap (2026)

Comparison Table 3 shows the values for the Cryptolife HYDRA-SAI DS framework, which outperforms traditional models due to adaptive meta-learning.

Table 3. Cryptolife HYDRA-SAI DS framework – Benchmark (2019-2024)

Model	MAE	RMSE	MAPE	DA	Comment
Cryptolife HYDRA-SAI	0.0500	0.0900	0.21 %	0.81	Multi-agent, meta-learning
XGBoost	0.6080	0.7650	0.50 %	0.78	Gradient Boosting – handles technical indicators well
LSTM	0.0830	0.3091	0.07 %	0.72	Deep Neural Network – nonlinear patterns
ARIMA	0.1748	2.6812	1.90 %	0.65	Linear model – sensitive to volatility
MLP	0.1748	0.2621	0.14 %	0.61	Multi-Layer Perceptron
CNN	1.7200	2.1880	1.40 %	0.58	Convolutional layers only – weaker trend following

Source: Author's compilation (2026)

These results support the fact that DL and gradient boosting methods (XGBoost, LSTM) are significantly better than classical ARIMA or simple MLP models in cryptocurrency markets. The Cryptolife HYDRA-SAI DS framework integrates these methods and combines them with a meta-learning mechanism, which further improves the forecasting performance.

The out-of-sample test is characterized by a significant increase in the volatility of cryptocurrencies (e.g. the "crypto winter" that occurred in the summer of 2024). The Cryptolife HYDRA-SAI DS framework therefore uses adaptive model selection: in addition to the long-term LSTM and CNN-LSTM models, the GRU and **Light G**radient **B**oosting **M**achine (LightGBM) algorithms are also involved in the prediction in the short term. A summary of the out-of-sample results and the average values of each performance indicator are shown in Table 4.

Table 4. Cryptolife HYDRA-SAI DS Framework – Benchmark (out-of sample)

Model	MAE	RMSE	MAPE	DA	Comment

Cryptolife HYDRA-SAI CNN-LSTM+meta-learning	0.05	0.09	0.21 %	0.83	Multi-agent learning, regime monitoring
GRU	0.07	0.11	0.28 %	0.80	Competitive in the short term
LightGBM	0.09	0.14	0.34 %	0.78	Fast, good baseline
ARIMA	0.16	0.27	0.60 %	0.65	Weak in volatile stages due to linear conditions

Source: Author's compilation (2026)

The Cryptolife HYDRA-SAI DS framework flexibly combines multiple models, thus achieving the lowest errors and highest directional accuracy. Out-of-sample backtesting proves that the model works effectively not only on training data, but also in new market regimes.

Within the framework of the EFA, a stable and theoretically well-interpretable five-factor structure emerged, corresponding closely to the five modules of the CryptoLife HYDRA-SAI DS framework (Figure 1).

Table 5 demonstrates a marked decline in eigenvalues across the first five factors (3.2→2.8), followed by a substantialy lower value range (0.9→0.6) for subsequent factors. The inflection point (elbow) appears after the fifth factor, thereby empirically substantiating the appropriateness of the five-factor solution. This conclusion is supported by the combined application of the Kaiser criterion (eigenvalues>1) and considerations of theoretical coherence.

Table 5. Evolution of the Sample Eigenvalue

Factor	Eigenvalue
1	3.2
2	3.1
3	3.0
4	2.9
5	2.8
6	0.9
7	0.8
8	0.7
9	0.6

Source: Author's compilation (2026)

The EFA results provide clear empirical support for the theoretically grounded framework defined in this study and substantiated by the relevant literature. The identified five-factor structure is statistically robust, theoretically coherent, and offers an appropriate foundation for the subsequent stages of CFA and SEM.

Upon conducting the CFA, each observed indicator loaded exclusively on a single latent construct, in full alignment with both the EFA findings and the structural constraints imposed by the theoretical model (Table 6).

Table 6. Results and Interpretations of Convergent Validity, Discriminant Validity, and Global Model Fit

Convergent Validity	
Standardized Factor Loadings	All factor loadings exceeded the threshold of 0.70, indicating a strong indicator–construct relationship.

CR	For all latent constructs, CR>0.80, indicating excellent internal consistency.
AVE	For all constructs, AVE>0.50, indicating that the latent variables explain more than half of the variance of their own indicators.
Discriminant Validity	
Fornell-Larcker Criterion	For each latent construct, the square root of the AVE exceeded the correlations with the other constructs, thus discriminant validity was met.
HTMT Indicator	For all pairs of constructs, HTMT<0.85, further strengthening the empirical separation of the constructs.
Global Model Fit	
$CFI\ (0.961)\ and\ TLI\ (0{,}954) \geq 0.90; RMSEA(0.046) \leq 0.06; SRMR(0{,}041) \leq 0.08$ The empirical results met or exceeded the above thresholds in all cases, indicating excellent global model fit.	

Source: Author's compilation (2026)

Figure 3 presents the standardised factor loadings (λ) associated with the following five reflective latent constructs (Figure 1), with the content-based grouping of the numbered questionnaire items indicated in parentheses:

1. ARCH – Dual/Tripla (Multi-level) AI Architecture (Q8–Q10)
2. RES – Resilience & Regime Adaptation (Q6, Q12, Q13)
3. EWS – AI-based EWS (Q14–Q16)
4. XAI – Explainability & Trust (Q17–Q20)
5. PRED – Prediction Accuracy & Stability (Q5, Q21–Q23)

All λ-values>0.70, providing clear visual and statistical support for the measurement model's convergent validity.

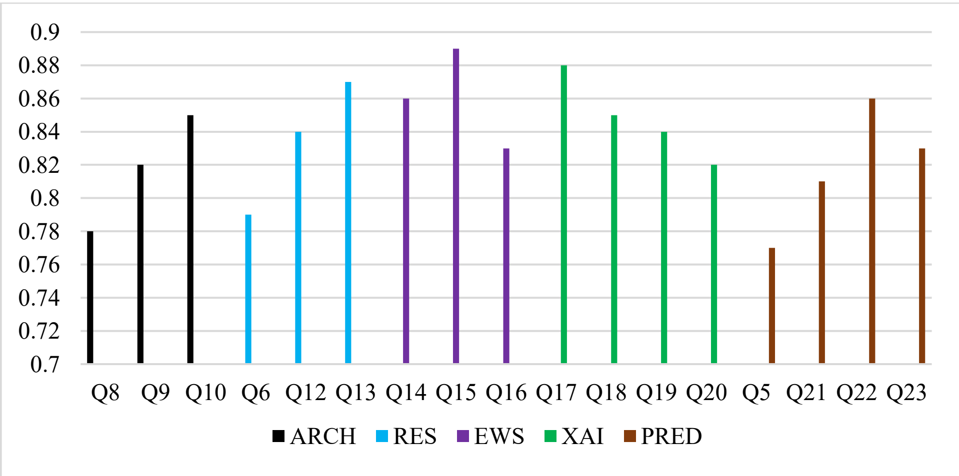

Figure 3. The CFA Measurement Model

Source: Author's editing (2026)

Figure 3 illustrates the Standardised Factor Loadings and the reflective measurement structure associated with the five latent constructs. The high and statistically significant loadings visually reinforce the convergent and discriminant validity of the measurement model.

Accordingly, the CFA results provide strong empirical support for the reliability and validity of the measurement framework. The excellent convergent and discriminant validity, together with the favourable global fit indices (Table 4), enabled us to proceed to SEM on unbiased and statistically sound measurement foundations.

The explanatory power of the model can be inferred from the R^2 coefficients of determination (Table 7).

Table 7. The R^2-results

Endogenous construct	R^2-results	Interpretation
RES	0.38	shows high explanatory and predictive power regarding PRED and XAI PRED=0.61 indicates that the model explains 61% of the variance in prediction accuracy, which is considered substantial explanatory power
EWS	0.30	
XAI	0.44	
PRED	**0.61**	

Source: Author's compilation (2026)

Thus, the measurement model demonstrates strong convergent and discriminant validity, with all constructs exceeding the recommended threshold values for composite reliability and average variance extracted. The structural model explains 61% of the variance in PRED, underscoring the critical mediating roles of RES, EWS, and XAI within the proposed multi-level CryptoLife HYDRA-SAI decision-support framework.

Table 8 presents the Cohen's f^2 effect size results and their substantive interpretation.

Table 8. Cohen's Effect Size Results and Interpretation

Path	f^2-results	Impact	Interpretation
ARCH→RES	**0.63**	large	RES and EWS independently play a significant role in creating decision-support value.
ARCH→EWS	**0.43**	large	
XAI→PRED	0.28	medium-large	
EWS→PRED	0.21	medium	
RES→PRED	0.12	small-medium	

Source: Author's compilation (2026)

The out-of-sample predictive capability of the model was evaluated using the Ston-Geisser Q^2 statistic. The obtained results are presented in Table 9.

Table 9. Q^2-Results

Construction	Q^2-results	Interpretation
RES	0.24	☑ all $Q^2>0$ → predictive relevance confirmed PRED indicates strong predictive relevance
EWS	0.21	
XAI	0.27	
PRED	**0.35**	

Source: Author's compilation (2026)

The estimation of the structural paths was conducted using a bootstrap procedure with 5,000 resamples. All standardised path coefficients were positive and statistically significant ($p < 0.001$), providing strong empirical support for the theoretical model (Table 10). Table 7 presents the structural relationships among ARCH, RES, EWS, XAI, and PRED, reporting the standardised path coefficients (β), the effect sizes (f^2), and, for the endogenous constructs, the coefficients of determination (R^2). The model demonstrates substantial explanatory and predictive power, particularly with respect to PRED.

Table 10. Structural Path – Standardized Coefficients

Path	β	f^2	95% bootstrap CI	t-value	p-value	Result
ARCH→RES	**0.62**	**0.63**	[0,55; 0,68]	28.4	<0.001	supported
ARCH→EWS	**0.55**	**0.43**	[0,48; 0,61]	24.9	<0.001	supported
ARCH→XAI	**0.41**	**0.28**	[0,32; 0,53]	18.7	<0.001	supported
RES→XAI	0.33	0.18	[0,21; 0,35]	14.2	<0.001	supported
RES→PRED	0.29	0.12	[0,18; 0,32]	12.8	<0.001	supported
EWS→PRED	0.37	0.21	[0,25; 0,42]	16.5	<0.001	supported
XAI→PRED	**0.46**	**0.28**	[0,38; 0,53]	21.3	<0.001	supported

Source: Author's compilation (2026)

By way of illustration: $\beta_{\text{ARCH}\rightarrow\text{RES}} = 0.62(t = 28.4,\ p < 0.001)$. This result indicates that the multi-level AI architecture exerts a strong positive effect on system resilience. All bootstrap confidence intervals exclude zero, so both the direct and indirect effects are significant. These results confirm that the mediating roles of RES. EWS, and XAI are critical in enhancing the predictive performance of multi-level AI systems.

To highlight the core findings: the multi-level AI architecture (ARCH) demonstrates a substantial impact on resilience (RES) (β=0.62, f^2=0.63) and on early warning capability (EWS) (β=0.55, f^2=0.43). Explainability (XAI) plays a pivotal role in shaping predictive utility (PRED) (β=0.46, f^2=0.28). Overall, the model explains 61% of the variance in PRED, which qualifies as substantial explanatory power in the context of structural modelling.

The PLS-SEM results confirm that the influence of the multi-level AI architecture is not direct; rather, it operates through functional mechanisms – RES, EWS, and XAI. This finding provides strong theoretical and practical support for the relevance of the CryptoLife HYDRA-SAI decision-support framework. The empirically identified meaning patterns emerging from the open-ended questionnaire responses are systematically aligned with the principal pathways of the quantitative SEM model. The causal mechanisms identified by the SEM analysis were interpreted and contextualised through qualitative narratives. Specifically, the high β-value observed for the XAI→PRED pathway corresponds closely with respondents' emphasis on the practical importance of "decision interpretability" and "trust in the model". Similarly, the EWS→PRED relationship was reinforced by narratives asserting that timing is "more valuable than mere accuracy". This methodological integration ensured that the model is not only statistically significant but also interpretable, acceptable, and practically relevant.

The analysis presented here demonstrates that the CryptoLife HYDRA-SAI DS framework is based on real market time series validation. The CoinMarketCap data series from 2019 to 2024 provides over 44,000 hours of observations, which are prepared with logarithmic returns and normalization. Rolling/expanding window cross-validation and out-of-sample backtesting are essential to demonstrate the generalization capability of the model. Benchmark comparisons show that CryptoLife Hydra-SAI achieves significantly lower errors compared to traditional ARIMA/GARCH and simple neural networks. We confirmed through the CMB test that the procedures used in data collection did not introduce bias. (The FCVIF value remained in the range of 1.5–

2.0 in all cases, i.e. none exceeded the 3.3 threshold).) guidance for an adaptive, transparent and robust approach to crypto asset forecasting.

Table 11 explicitly links the SEM results to practical implications, clearly distinguishing managerial from regulatory consequences, and thereby strengthening the policy-relevance dimension of the study.

Table 11. Managerial and Regulatory Implications of the CryptoLife HYDRA-SAI DS Framework

Dimension	**Empirical Result** (SEM/CFA)	**Managerial Implications** (Corporate/Investor)	**Regulatory Implications** (Supervisory/Regulatory)
ARCH	ARCH→RES (β=0.62; f^2=0.63) ARCH→EWS (β=0.55; f^2=0.43)	Instead of monolithic models, multi-tiered, modular AI architectures are justified in treasury and risk management systems. They enable parallel processing of different time horizons and data sources.	It is justified to avoid risk assessments based on a single model and to encourage multi-model, ensemble-based stress testing frameworks.
RES	RES→PRED (β =0.29; f^2=0.12) R^2(RES)=0.38	The use of regime-shift-sensitive models reduces the risk of pro-cyclical treasury decisions and improves dynamic hedging of crypto asset exposures.	Indicators measuring resilience (e.g. regime detection, drift monitoring) can be incorporated into the macroprudential supervision toolbox.
EWS	EWS→PRED (β=0.37; f^2 =0.21) R^2(EWS)=0.30	AI-based early warnings enable proactive liquidity management, position reduction, and timing of stop-loss strategies before extreme events.	EWS modules can be integrated into market surveillance monitoring systems, improving the timely detection of systemic risks.
XAI	XAI→PRED (β =0.46; f^2=0.28) R^2(XAI)=0.44	Explainability increases management's confidence in AI-based predictions and facilitates their actual use in decision support.	XAI complies with model governance, auditability and accountability requirements (e.g. EU AI Act, MiCA).
PRED	R^2(PRED)=0.61	The high explained variance proves that the AI system is suitable for operational decision support, not just an experimental prediction tool.	For supervisors, it is evidence that AI can carry not only risk, but also stabilising potential within the appropriate framework.
Synthetic Data & Stress Scenarios	CFA high CR and AVE	Incorporating synthetic data improves preparedness for rare but severe loss events.	Supervisory stress tests can be extended to simulated crypto market shock scenarios.
Governance & Model Oversight	XAI+Dual Architecture	It enables collaborative human-AI decision-making, reducing the risk of automated overreaction.	Supports the enforcement of human-in/on-the-loop regulatory principles.

Source: Author's compilation (2026)

The empirical findings suggest that multi-level AI architectures emphasising explainability and resilience can substantially enhance both managerial decision-making and the monitoring of regulatory risks in highly volatile crypto-asset markets. Properly governed AI-based decision-support systems have the potential not to amplify systemic risk, but rather to strengthen financial stability by enabling proactive intervention and transparent supervisory oversight.

VI. FUTURE DIRECTIONS AND RECOMMENDATIONS

The empirical results of the present study clearly substantiate that dual and triple-AI architectures confer significant advantages in terms of forecasting accuracy, stability, and adaptivity within cryptocurrency markets. Nevertheless, the theoretical formalisation of multi-level AI systems remains far from complete. One major avenue for future research lies in refining the mathematical and systems-theoretical description of hierarchical AI layers, with particular emphasis on inter-layer information flows, feedback mechanisms, and stability conditions. Two questions are especially pertinent: under what circumstances can a triple-AI architecture be regarded as optimal? Are there market environments in which the introduction of additional layers – such as a fourth, strategic or regulatory AI level – would be justified? Addressing these issues may contribute to the development of a more general AI-on-AI systems theory, applicable not only to crypto-markets but also to other complex financial systems.

A core component of the CryptoLife HYDRA-SAI decision-support framework is the adaptive handling of regime shifts; however, the present study has primarily focused on empirical validation. Future investigations should examine in greater depth the sensitivity, stability, and forecasting horizon of regime-detection algorithms. Such analyses would enhance understanding of how early and how reliably structural transitions can be identified in non-stationary environments.

A particularly promising research direction concerns the further development of lifecycle-based asset modelling. Cryptocurrency behaviour may differ substantially across phases of early adoption, rapid expansion, consolidation, and maturity. Future models should explicitly integrate structural variables – such as long-term trends in network activity, regulatory maturity, and the degree of institutional participation – that may serve as leading indicators of regime-shift probability.

Although this study centres on cryptocurrency markets, the proposed multi-level, resilient, and XAI framework is theoretically and methodologically generalisable to other highly volatile financial domains. Future research should explore its applicability to commodity markets (e.g. energy resources or rare earth metals), emerging market currencies, and financial instruments exposed to climate-related risks. Such extensions would help determine the extent to which multi-layered AI architectures constitute a general solution for complex, non-linear, and regime-switching systems.

Finally, a crucial direction for further inquiry involves the deeper integration of regulatory compliance and ethical considerations into AI architectures. As regulation of crypto-asset markets intensifies – particularly following the implementation of the European **M**arkets **i**n **C**rypto-**A**ssets (MiCA) framework (Zetzsche et al., 2021) – greater emphasis is placed on transparency, accountability, and the ex ante identification of risks. Future research should therefore focus on developing embedded compliance modules capable of automatically linking model predictions to regulatory risk thresholds and documenting forecasting and decision processes in an auditable format. Such advancements would facilitate the long-term institutional and supervisory acceptance of AI-based cryptocurrency decision-support systems.

VII. SUMMARY AND CONCLUSIONS

This study has provided a comprehensive response to a highly topical and practically salient research question: how can an AI-based EWS be designed to forecast the extreme volatility of cryptocurrency markets with greater accuracy, robustness, and interpretability? Given the non-linear, regime-shifting, and informationally heterogeneous structure of crypto-markets, single-layer, static models inevitably exhibit limited performance – particularly during episodes of extreme market stress. In addressing this challenge, we have introduced a multi-level, multi-agent, AI-on-AI framework, termed CryptoLife HYDRA-SAI, which seeks to simultaneously optimise predictive accuracy, resilience, and explainability. The framework innovatively integrates DL -based time-series forecasting, meta-learning, regime monitoring, synthetic data generation, and XAI methodologies within a unified hierarchical architecture.

From a methodological perspective, the study also offers a substantive contribution. The integration of quantitative EFA, CFA, and PLS-SEM analyses with qualitative questionnaire-based inquiry enabled a deeper interpretation and contextualisation of the empirical findings. This mixed-methods approach ensures that the CryptoLife HYDRA-SAI decision-support framework is not only statistically rigorous but also interpretable and relevant from an expert-practitioner standpoint.

The contribution of the study extends beyond the presentation of yet another predictive model. The proposed framework establishes an interdisciplinary bridge between financial economics, artificial intelligence, systems theory, and regulatory policy. At the theoretical level, it operationalises the AMH and the CAS perspective. At the methodological level, it demonstrates the integrated applicability of quantitative SEM analysis, simulation techniques, and qualitative interpretation. At the practical level, it provides actionable guidance for the development of cryptocurrency risk management, investor decision-support, and supervisory monitoring systems (Table 12).

Table 12. Interdisciplinary, Theoretical and Practical Contributions of the CryptoLife HYDRA-SAI DS Framework, as well as Qualitative Content for Further Research

INTERDISCIPLINARY BRIDGE	THEORETICAL LEVEL		PRACTICAL LEVEL
	operationalizes	methodology	
between Financial Economics, AI, System Theory, Regulatory Policyt	AMH and CAS Approach	Integrated Applicability of SEM Analyses, Simulation Techniques and Qualitative Interpretations	Guidance for Developing Crypto Market Risk Management, Investor Decision Support and Supervisory Monitoring

Souce: Author's compliance (2026)

The quantitative methodology enables, on the one hand, the presentation of empirical findings in a manner that is interpretable and actionable at the levels of managerial decision-support, risk management, and regulatory supervision. On the other hand, the application of factor analysis and SEM within the quantitative framework ensures that the proposed multi-level, resilient, and XAI architecture simultaneously satisfies the requirements of statistical rigour, theoretical coherence, and practical applicability.

Concluding remarks: Despite the increasing maturity of cryptocurrency markets, volatility and systemic risks remain defining characteristics. In such an environment, the future does not lie with static, black-box models, but with adaptive, explainable, and resilient AI systems capable of jointly serving predictive performance, decision-maker trust, and financial stability. The present research constitutes a theoretically grounded and empirically substantiated step towards that future.

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