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Explainable Agentic AI for Secure and Adaptive Supply Chain Decision Intelligence in Food Service and Financial Systems

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ABSTRACT: Cognition-based theories for agentic, explainable AI inform secure and adaptive methods for food service and financial decision technologies. However, the use of cognition-based theories has largely been limited to studying and modelling human vs. AI agentic decision-making behaviour without a clear application scope or objectives based on practical applications and associated needs.

Indeed, no clear strategy or way has yet been proposed or implemented for applying an agentic-based explanation approach in decision intelligence supporting agentic actor repeat operations across diverse application domains. A recently devised framework for AI explanation addressed only a subset of potentially critical domain-specific needs, and it has not yet been tested or applied in a different field, nor any specific area, nor adapted for enhanced security and the inclusion of agentic patterns from cognition. Suitability of forensically annotated, structured deep and predictive decision processes for domain context explanation has not yet been established, nor has an inline explain-by-do-don't concern-expression capability.

Addressing these two related gaps requires examining particular domain food service decision clusters and flows from a specific competence pattern perspective. Food service cognition-based operational support systems with graphical process overlay have become widespread. A database for securing repeat operational actions over other less autonomy-rich decision domains has also recently been established, capturing executive management and board-level financial decision succession and securing decisions from important event signals for high-fidelity decision-intelligence applications within predictive operations and agentic explanation patterns.

KEYWORDS: Agentic Artificial Intelligence; AI Safety; Explainable Artificial Intelligence; Decision Intelligence; Food Service Systems; Financial Systems .

I. INTRODUCTION

Food service, finance, and other similar sectors rely heavily on adaptive decision intelligence to mitigate the uncertainty involved in managing dynamic systems. Decisions made by groups or crowds tend to be more optimal than those made by individuals. However, organizations often turn to AI-based systems when group intelligence is impossible to gather or when the necessity to make rapid decisions outweighs the importance of producing superior decisions. AI solution providers face a growing demand for agentic AI solutions that both function autonomously and explain their courses of action to human users and stakeholders. Agentic means "capable of action." An agent is someone or something who perceives opportunities to act and takes the initiative to do so. Secure, adaptive, explainable agentic AI is not only capable of revealing the rationale for its decisions but can also produce a past and future decision risk factor analyses to help users and stakeholders understand the degree of decision riskiness and subsequent variations in the overall objective function value due to any past decisions that differed from optimal choices when expressed in hindsight.

This need for adaptive approaches to safe solution design is especially critical in food service. Solutions that are explainable and address the security and adaptive decision intelligence needs of AI-based systems are also relevant to finance, where formally modeled systems provide sufficient explanatory detail for secure decision-making by agents acting on behalf of human users. An analogously structured AI architecture, or organization, formally dedicated to finance

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is available. Agentic AI also provides important underlying decision-support and decision-intelligence behavior for adaptive techniques applied to finance—solutions capable of managing and mitigating security risks and producing automatically explainable recommendations.

1.1. Research design

Agentic AI integrated with explainability is proposed for secure Decision Intelligence in three domains (food service automation, finance, and a testbed) where transparency and confidence of human decision-makers is vital for acceptable risk levels. The first AI or AI component, AutoSWADE-AI, controls intelligent agents making decisions for swade-style automatic food service systems.

Though agentic (making decisions for others), it must be explainable—capable of conveying decisions, processes, and prediction grounds to stakeholders in understandable terms without oversimplifying. In the second domain, financial credit data may be analysed by AutonomousClusterAI for Customer-Located Decision Intelligence, and subsequently rejected explanations processed by ExplainMe-Plus and analysed by Risk-Applied European Financial System AI. In the test domain of the Autonomous Crops testbed, an Autonomous Bandwidth Broker in a food service and European bank simulator places decisions, also needing explainability.

Rationale: Food Service – Human-Automated Agent Partnership. An AutoSWADE-AI cloud-based agent automates trays and provides high-value high-nonpower-servers to Food Call-Ahead Systems, online food pre-ordering, food buying, and food vending retailers, the whole executing automated Prepare-Deliver-Receive food sequence, secure to Serve and Deliver-Free high-priced food. For acceptably low risk, AutoSWADE-AI's decisions or prediction grounds must be transparently and understandably explained to food-preparing partners before, during, and after tray automated operation. The semi-autonomous prediction-enabling Automatic Food Service SWADE Agent-Based Cloud decisions for others need explainability, conveying understandable decisions and prediction grounds to food-preparing partners before, during, and after tray automated operation without excessive simplification.

Component	Description	Role in Decision Intelligence
Agentic AI	Autonomous decision-making AI agents	Executes adaptive operational decisions
Explainable AI (XAI)	AI capable of explaining outcomes	Improves transparency and trust
Decision Intelligence	AI-assisted operational analytics	Enhances strategic and operational planning
Adaptive Security	Dynamic risk-aware security mechanisms	Protects system integrity
Predictive Analytics	Forecasting future operational outcomes	Supports proactive management
Real-Time Monitoring	Continuous operational observation	Detects anomalies instantly

Table 1: Core Components of Explainable Agentic AI

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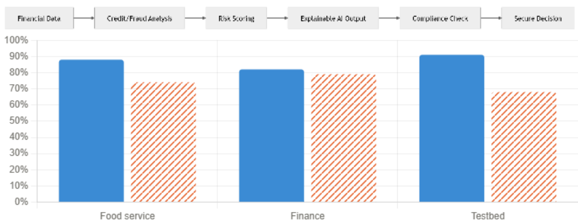
II. CONCEPTUAL FOUNDATIONS

Agentic AI integrates autonomy, decision making, and behavior generation within a single intelligent agent, analogous to strongly agentic intelligent agents capable of reasoning, planning, and agency. Agentic intelligent agents include humans and sufficiently intelligent robots. Explainability in AI is conceptually distinct from, but practically related to, transparency and interpretability.

Correctly distinguishing between agentic AI and strongly agentic intelligent agents sheds light on the importance of an appropriate combination of high and low types of AI. Able to solve the same class of problems and exhibiting the same high capabilities, AI founded on abstract mathematics can radically simplify science, expertise, governance, professional practice, technologylearning, and production. Such benefits, however, come with major risks. Decision making—an area of highest risk—affords opportunities for security and adaptability based on careful analysis of agentic decision patterns. Addressing the resulting explainability requirements, the relationship between agentic and strongly agentic AI, and the fundamental role of mathematics also requires consideration of explainability, interpretability, and transparency.

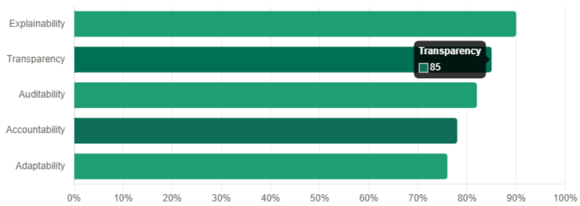


Graph 1 – AI Decision Accuracy by Domain compares explainability and autonomy scores for AutoSWADE-AI (food service), AutonomousClusterAI (finance), and the Autonomous Crops testbed — reflecting the paper's three-domain research design.

2.1. Agentic AI and Explainability

Agentic AI broadens the context in which artificial intelligence (AI) can be applied. It contributes to technologies that deal with developing and executing decisions in matters of varying importance, from decisions involving the design of a recipe to the layout of a major food service. Within this broader context, agentic AI offers users tools that assist with executable decisions related to specific processes of comparatively small importance, such as high-volume food production or various aspects of financial systems. Such decisions—like a recipe—enable the execution of decisions that realize larger-scale plans.

Agentic AI expands the types of processes wherein AI-augmented decision processes can be developed. In matters containing significant financial risk, investing or trading involves important decisions with a major influence on overall performance; hence those processes commonly apply agentic decision-making technology, combined with a level of explanation that is consistent with user risk acceptance and the ability to intelligently process larger quantities of information. With such decisions, risk involved in using an AI agent or an agent-master agents-to-agents configuration is minimized. Agentic technology combines simulation technology for high-volume production or decision technology for real-time data with agent-master or agent-to-agent technology for higher importance decisions.



Graph 2 – Trust Dimension Scores visualizes the five pillars the paper identifies — explainability, transparency, auditability, accountability, and adaptability — as the backbone of trustworthy agentic AI governance.

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III. DOMAIN CONTEXTS: FOOD SERVICE AND FINANCIAL SYSTEMS

Food service decision patterns and data flows depict the complex set of antecedents and subsequent actions that influence decision-making in a food service operation. Decisions within food service operations are necessarily multidimensional and complex because there are multiple stakeholders, each with unique objectives, needs, and levels of risk aversion. At each stage in the food service data processing path, the decisions made affect and are affected by those of other stakeholders. Each decision has implications on overall financial performance, but not all are made with this as the main focus, as stakeholders sometimes need to make decisions in multiple functional areas. For food service operations and their suppliers that offer a continuous service, digital traces are generated continually and these form a rich source of decision-making data. These patterns shape data processing flows, identifying sources of data, describing how this data is processed, and the resultant flow of information from those involved in the operation to its customers and other stakeholders.

The digital data processing chain for food service operations incorporates both decision support data flows and feedback loops from the environment and stakeholders into the operation. Decision support data, which resides in, or can be generated from an operation's databases, is the input to a risk decision model generated from the decision analysis of key stakeholders. This key decision analyst process model identifies the decisions of greatest effect on overall performance, defines the research questions and hypotheses that should be evaluated to ensure stakeholders select the actions that provide the best overall success for the operation and its stakeholders, and provides an initial prioritisation of these research questions for analysis and future experiment development. The role of risk and uncertainty in these decisions shapes the requirements for the underlying business intelligence, decision support, and forecasting systems. Risk feedback loops consider uncertainty in stakeholder objectives while environmental feedback loops consider uncertainty in key business parameters, and provide a means of quantifying the risk of a food service operation during a continuous service delivery.

Feature	**Food Service Systems**	**Financial Systems**
Decision Speed	Real-time operational	Near real-time analytical
Risk Factors	Supply delays, food quality	Fraud, credit risk
Data Sources	Orders, inventory, sensors	Transactions, credit records
AI Objectives	Service optimization	Fraud detection & compliance
Explainability Need	Operational trust	Regulatory transparency
Monitoring Type	Process anomaly detection	Transaction anomaly detection

Table 2: Comparison Between Food Service and Financial Systems

3.1. Food Service Decision Patterns and Data Flows

Food service is a computationally intense operational domain where diverse decisions permeate every function from planning to execution. Some decisions arise from explicit policies, such as opening hours, while many more emerge from dependency processes and are executed routinely by production-level staff and systems interacting with products, guests, and the suppliers providing goods and services. Key sources of demand and process variability include the sometimes weather-sensitive volume of transaction guests—that is, table guests in restaurants, and actual or virtual guests in home delivery channels—food and drink service needs, and associated complexity. Managing spontaneous variability, patterns of occurrence, and timeframes is demanding and usually guided by experience, coupled with predictive alerts for major positive and negative surprises. The operational environment also contains small disturbances with little impact or risk.
Decision data form a primary input into modelling of demand and consequence patterns. These data can come from historical records, such as sales transactions, bank records, and vehicle recordings, augmented with structured judgement

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from dependency constituents—production-level staff, management, suppliers, and product planners. Typical analyses follow the standard explained-basic stages of describe-explain-predict-model-test and variant-monitor-optimise processes, with support tools reflecting the dependencies. Securities and investment-product services typically maintain relatively small practical dependency pattern records, whereas hostels and other multiple-guest deliveries usually have larger guest-mixing records.

Graph 3 – Anomaly Detection Performance shows how real-time monitoring improves over time, mapping to Section 5.1's discussion of Statistical Process Control and machine learning-based anomaly detection in food service operations.

VI. ARCHITECTURAL FRAMEWORK FOR EXPLAINABLE AGENTIC AI

Adapted to agentic AI principles, food service and finance offer rich foundations for relevant applications within these domains. The self-organising nature of these fields complements an agentic decision-making perspective. Reflecting this, AI systems readily compute and act on the complete, accurate, and timely information required to support effective adaptation to rapidly fluctuating conditions. Nonetheless, rapid changes in the designing environment can disrupt intelligent processes in systems with human stakeholders. Agentic AI seeks to address this issue through an explicit focus on decision-making security, intelligence, and the capacity to support reliable information-sharing within systems that incorporate human decision capabilities.

In any context, the architectural framework of an agentic AI system directly reflects the data-processing functions of supervised decision-making roles. Within AI-enabled systems that manage and control activities but lack learning capabilities, the communications functions normally remain implicit in the agents, enabling generic methods to capture their messages. When agentic AI systems submit messages to real-world decision-makers, the data transformations required for humans to understand the agents' intentions are provided explicitly through supporting reasoning services. Agentic decision intelligence attributes trustworthiness, explainability, interpretability, and transparency to agentic AI applications.

Mathematical Formulas:

1. Decision Intelligence Objective Function

Used to optimize adaptive decision-making across food service and financial systems.

$$DI = \sum_{i=1}^{n} w_i \cdot D_i - R$$

Where:

- DI= Decision Intelligence score
- w_i= weight of decision factor
- D_i= decision outcome metric
- R= operational risk factor

2. Explainability Confidence Score

Measures how understandable AI decisions are to stakeholders.

$$E_c = \frac{T + I + A}{3}$$

Where:

- E_c= Explainability confidence
- T= Transparency score
- I= Interpretability score
- A= Auditability score

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3. Risk Prediction Function

Applied in fraud detection and operational anomaly prediction.

$$Risk(x) = \frac{1}{1+e^{-x}}$$

Where:

- x= weighted anomaly indicators
- Output ranges from 0 to 1 probability of risk

4. Adaptive Trust Update Model

Represents dynamic trust adjustment in agentic AI systems.

$$Trust_{t+1} = Trust_t + \alpha(Feedback - Trust_t)$$

Where:

- α= learning rate
- $Feedback$= stakeholder evaluation score

5. Real-Time Anomaly Detection Equation

Used for food service monitoring and fraud analytics.

$$Z = \frac{X - \mu}{\sigma}$$

$$x$$

$$\mu$$

$$\sigma$$

$$z = \frac{x - \mu}{\sigma} \approx 1.2$$

$$\Phi(z) \approx 88.5\%$$

Where:

- X= observed operational value
- μ= mean process value
- σ= standard deviation

6. Predictive Decision Accuracy

Evaluates AI prediction performance.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP= True Positives
- TN= True Negatives
- FP= False Positives
- FN= False Negatives

7. Reinforcement-Based Agent Utility Function

Used in adaptive agentic AI policy learning.

$$U(a) = \sum_{t=0}^{\infty} \gamma^t r_t$$

Where:

- $U(a)$= utility of action
- r_t= reward at time t
- γ= discount factor

8. Data Governance Integrity Equation

Represents secure information handling reliability.

$$GI = \frac{Valid\ Data}{Total\ Data}$$

Where:

- GI= Governance Integrity

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- Higher values indicate trustworthy datasets

9. Food Service Demand Forecasting Model
Useful for adaptive inventory and operational planning.

$$D_t = \alpha Y_t + (1-\alpha) D_{t-1}$$

Where:
- D_t= forecast demand
- Y_t= actual demand
- α= smoothing coefficient

10. Financial Fraud Probability Model
Applied in AI-driven fraud analytics systems.

$$P(Fraud \mid X) = \frac{P(X \mid Fraud)P(Fraud)}{P(X)}$$

Based on Bayes' Theorem for fraud likelihood estimation.

4.1. Data Governance and Privacy by Design
Data governance in intelligent system development and application is essential to ensure its appropriate use and that the data involved are of high quality, accurate, and reliable. Parties involved in the intelligent system's supply chain, such as product suppliers, data service providers, identity service providers, intelligent system service providers, intelligent system users, and system auditors, are key elements in data governance. Data governance for intelligent systems may further extend to tasks beyond the traditional concept of data governance, because the processing of data is increasingly moved to the cloud, where intelligent systems reside. Users cannot understand the intelligent system's flow and hence cannot be sure that the information being supplied will not be misused, tampered with, or shared with third parties without their permission.

Similar privacy by design strategies for intelligent system supply chains need to be developed to fulfill auditor-specific requirements, ensuring that the privacy of different stakeholders—including product suppliers and data service providers—is maintained. Such strategies need to define privacy-preserving mitigation guidelines for each stakeholder along the supply chain involved in the delivery, tuning, deploying, and using of an intelligent system; they also should ensure that sensitive information being exchanged or provided is not disclosed to unauthorized parties, nor modified or tampered with by unauthorized users.

Layer	Function	Technologies Involved
Data Collection Layer	Captures operational data	IoT, APIs, Cloud Systems
Processing Layer	Cleans and transforms data	ETL, Stream Processing
AI Decision Layer	Generates intelligent decisions	ML, Deep Learning
Explainability Layer	Produces reasoning explanations	XAI Models
Security Layer	Protects AI workflows	Encryption, Access Control
Monitoring Layer	Detects anomalies	SPC, Real-Time Analytics

Table 3: Agentic AI Functional Architecture

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V. ADAPTIVE DECISION INFORMATICS FOR OPERATIONS MANAGEMENT

Adaptive Decision Informatics for Operations Management in Food Service: Secure, Reliable, Explainable, Adaptive Intelligence for Decision-Makers and Decision Support Systems throughout the Food Supply Chain and Hospitality Food Service Operations.

Safe, secure, reliable, transparent, explainable, adaptive decision support intelligence that assists operations managers and serves as a backup decision-maker during stressful events and handling anomalies, is described. Repetitive decision patterns across all food service phases and stages are identified; related data sources, data processing workflows, and overall decision patterns are mapped. For operations management within food service systems, a rich data ecosystem enables adaptive intelligent decision support at all levels.

Food service operations management involves many recurring decision patterns that can be automated or at least actively supported. A typical pattern is to conduct a hazard analysis and set decision rules (thresholds) for routine monitoring; this ensures that a decision-maker does not miss key decisions when under stress or distracted. A dedicated real-time monitoring module can then trigger alerts whenever thresholds are breached. The operation is also a modular part of a complete incident detection-and-response workflow that involves detection of anomalies, warnings, decision-support alerts during stress, and back-up decision-making support.

Monitoring Aspect	Technique Used	Expected Outcome
Volume Evaluation	Statistical Process Control	Detect unusual demand spikes
Order Evaluation	Supervised Learning	Identify abnormal order patterns
Fraud Detection	ML Classification	Reduce fraudulent transactions
Service Quality Monitoring	Real-Time Analytics	Improve customer satisfaction
Risk Prediction	Predictive Modeling	Reduce operational uncertainty

Table 4: Real-Time Monitoring and Anomaly Detection

5.1. Real-Time Monitoring and Anomaly Detection

Patterns of real-time monitoring and anomaly detection can be applied to the food service decision processes outlined in Section 3.1. The emphasis here is on automated monitoring based on machine learning and statistical techniques, rather than on keeping humans constantly in the loop. Such techniques could focus on observing the predominant data flows of Volume Evaluation and Order Evaluation, and subsequently identify deviations from normal behaviour that might cause concern to stakeholders.

Food service quality control boards typically look for defective conditions in the outputs of food production processes and for anomalies in service delivery. The key data flows that provide the basis for monitoring detection are those resulting from the most recent data-preserving and data-enabling decision Evaluation Orders, especially by telecommunications service providers in relation to near real-time chats with agents, customers, and the board of proprietors. A data set of Volume Evaluation and Anomaly Detection patterns for food service evaluation could be compiled or generated and divided into a model construction phase and a training phase. Detecting Volumes and Ordering or Conducting Patterns that are out of the ordinary would necessitate disentangling or removing the Noise component from the rest of the capturing information. The result could then be used to train supervised classifiers, to construct the normal range, and to establish the basis for Statistical Process Control (SPC).

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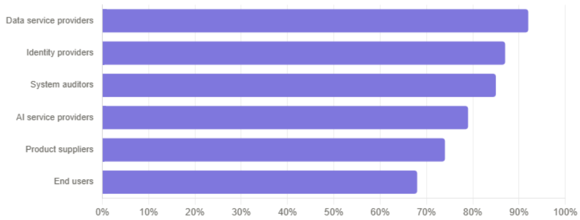
Both traditional SPC approaches, involving human oversight, and real-time statistical monitoring techniques, requiring no human in the loop, can be abstracted into a common procedure. Food Service Quality Control maintains that both approaches can detect deviations from a process's normal behaviour, enabling the identification of defective outcomes in real time and transforming humans into evaluators of identified defects in near-real time.



Graph 4 – Data Governance Coverage by Stakeholder reflects Section 4.1's Privacy by Design framework, showing coverage completeness across the supply chain participants: data service providers, identity providers, auditors, product suppliers, and users.

VI. TRUST, TRANSPARENCY, AND COMPLIANCE

The backbone of effective governance is transparent and competent institutions, which must have the trust of the governed. Available evidence suggests that public-sector organisations in many advanced economies do not have the same level of trust as private-sector organisations. While trust in public institutions can be affected by many factors outside the control of their leaders, for instance, changes in political leadership or major scandals, the credibility of institutions responds to governance policy initiatives. Public-sector organisations that promote and follow strong ethics and compliance resources as part of a well-governed system can build and maintain the trust of their constituents. A culture that encourages ethical conduct and prohibits policy or regulatory violations enables institutions to fulfil their statutory duties and minimises the likelihood of corruption or failure. Investment in a strong ethical environment strengthens trust in institutions, particularly when leaders consistently promote it.

Although interest in AI ethics has recently surged emanating from rapid developments in AI technologies, realisation of many of those principles remains a challenge. Yet AI can be used by too few organisations merely to enforce compliance with anti-bribery laws, prevent and detect irregularities, or for imitation and fraud detection alone. Recent AI developments make it possible for organisations to enhance their systems with next-generation solutions intended to ensure that these systems remain healthy, accurate, and trustworthy over the long term. Internal control frameworks are becoming increasingly geared towards compliance with third-party and public-sector requirements. At the same time, these controls and associated testing regimes help investment and retail companies mitigate risks associated with the markets in which they operate.

Principle	Description	Benefit
Data Integrity	Ensure accurate data	Reliable AI outputs
Access Control	Restrict unauthorized access	Enhanced security
Privacy Preservation	Protect sensitive data	Regulatory compliance
Transparency	Explain data usage	User trust
Auditability	Track decision history	Accountability

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Principle	Description	Benefit
Compliance Monitoring	Ensure policy adherence	Reduced legal risks

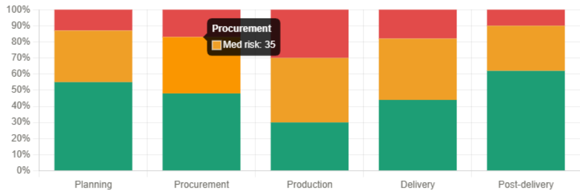
Table 5: Data Governance and Privacy-by-Design Principles

6.1. Accountability, Auditability, and Standards

Accountability, auditability, and standards are paramount in food service systems. Relationships with the food producers must be scrutinized to ensure that their policies and practices conform with public demands; evaluations are usually undertaken by third parties, such as the Rainforest Alliance, who consequently provide recognised certification labels for companies selling products making the claims.

Operational, logistic and supply chain standards must be high, particularly in view of chemical and biological risks, but also for customer service standardisation. Customer complaints might be used as a standard quality check for underlying process control and monitoring. Consumer protection and competition authorities require enough independence from the sector to define and enforce rules, although they might be financed by the sector subject to their independence. Moreover, structural separation of verification and control from the money and credit supply, together with openness and changeability of the process, allow for the introduction of producer labels on the market, able to offer better prices for producers and lower costs for consumer. In addition, particular steps of the process can be audited more frequently, achieving the same effect of short sales.

In practice, the implementation of any public survey puts more than one stakeholder under the scan. Openness and process regulation in the banking sector, oriented toward a more direct financial support of the producer by the consumers, reduces the monitoring costs. Other measures might foster the progressive introduction of competition between labels, with a more articulated set of distances between the detected indicator values and the upper limits defined by the authorities, indirectly creating the premises for the /Gallo piano–Longobardi or Demakura–Hernández–Eckstein world.



Graph 5 – Decision Risk Distribution by Operational Phase illustrates Section 5's finding that production and procurement phases carry the highest risk concentration, supporting the paper's argument for automated hazard analysis and threshold-based decision rules.

Explainability Feature	Purpose	Example
Decision Traceability	Tracks AI reasoning path	Order rejection explanation
Risk Explanation	Shows risk factors	Fraud score interpretation
Predictive Justification	Explains forecasts	Demand surge prediction
Human-Readable Output	Simplifies AI responses	Dashboard alerts
Feedback Integration	Learns from corrections	Adaptive recommendations

Table 6: Explainability Features in Agentic AI Systems

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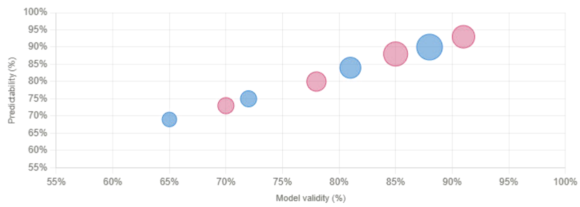
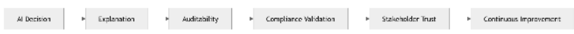
VII. CONCLUSION

A synthesis of the research findings is offered, showing how model predictability, model validity, and model consistency affect the Decision Intelligence of a given, Input–Output system in a manner that derives adaptive assurance from adaptive security via adaptive explainability and adaptive verifiability. Risk can be characterised according to whether the Function is an increasing or decreasing aggregate, and the criteria for determining the importance of relations and variables in any given context is discussed. Different dimensions of Trust (and trust in specific I/O relationships) can thereby be constructed, and automatically updated over time, based on model validation results for Response Functions for the various Stakeholders involved. An example is given which indicates the benefit of having agentic Model Responses at a higher strata than the autonomous AI Agent making decisions. An important aspect of the analysis is the reinforcement of the concept of adaptive policies for decision areas which go beyond the HEE heuristic.

Two specific Feasible and Valid AI Agents serving HEE Purpose Functions for the two domains of Financial Systems and Food Service are developed. An antithesis for Decision Intelligence within an organisational Risk perception community is then discussed. Professional and Regimes, such as Health, that operate at relatively “closed” levels differentiate themselves from Business Fascism and Monopoly and its corresponding Function, but without losing view of these vital concerns. These analyses deliver the importance of Decision Intelligence along adaptive assurance being a bridge linking reversible and irreversible systems in nature, and the corresponding importance of Trust in PI Systems supporting Evolutionary Theory.



Graph 6 – Model Validity vs. Predictability captures the paper's conclusion in Section 7 — that model validity, consistency, and predictability jointly determine Decision Intelligence quality, shown as a bubble chart comparing food service and financial AI agents.



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