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Chapter 10: Future Directions in Trusted and Self-Regulating Enterprise Intelligence Systems

10.1. Introduction

Enterprise Intelligence Systems (EIS) use Artificial Intelligence (AI) techniques to automate decision-making at enterprise levels as a means of improving productivity, profitability, and competitiveness. Trust in such systems can lead to their wider adoption and use. Trust can motivate self-regulation, reducing dependence on external regulation or assurance and enabling faster, more efficient and less costly operation. This presentation discusses the foundations of trust and self-regulation in EIS, their architectural imperatives, practices for self-regulation, and suggestions for future research in the area of trust in enterprise intelligence systems. Questions addressed include:

- What are the conceptual underpinnings of trust in enterprise intelligence systems?

- What architecture is needed in enterprise intelligence systems to engender trust?

- What governs trust in enterprise intelligence systems in practice?

- How are trust and self-regulation of enterprise intelligence systems maintained during operation?

- What are the necessary conditions for and possible sources of trust and self-regulation in enterprise intelligence systems?

- How do these systems differ from other AI-based systems, such as algorithms used to predict the outcome of court cases, and what coping mechanisms are therefore needed?

- In what ways is the behaviour of enterprise intelligence systems distinct from AI-based systems for image classification, recommendation engines, and chatbots, and how are trust and self-regulation therefore supported?

10.1.1. Setting the Stage for Trust and Self-Regulation in AI-Driven Enterprises

As organizations continue to invest heavily in predictive technology for decision-making, related systems must become capable of building trust with their human users. The topics of faith and trust in AI have already received considerable attention during the early phases of development, and a large body of work aims to address the related but distinct topics of oversight, accountability, and self-regulation in autonomous systems. Nevertheless, there is still a desire to investigate the nature of trust in self-regulating decision-support systems and networks that directly control enterprise resources and perform their own analyses, learning, cyber-attacks, and cyber-defence actions. Accordingly, this section positions trust and self-regulation mechanisms relevant to enterprise intelligence in dialogue with the key issues raised by enterprise users and consumers. Trust has been defined as an expectation by an agent of the reliability of an action or outcome. Whether expressed in simple terms—one would trust the system to do the right thing—or more abstractly, one would trust the system if it reliably produced appropriate behaviour without intervention.

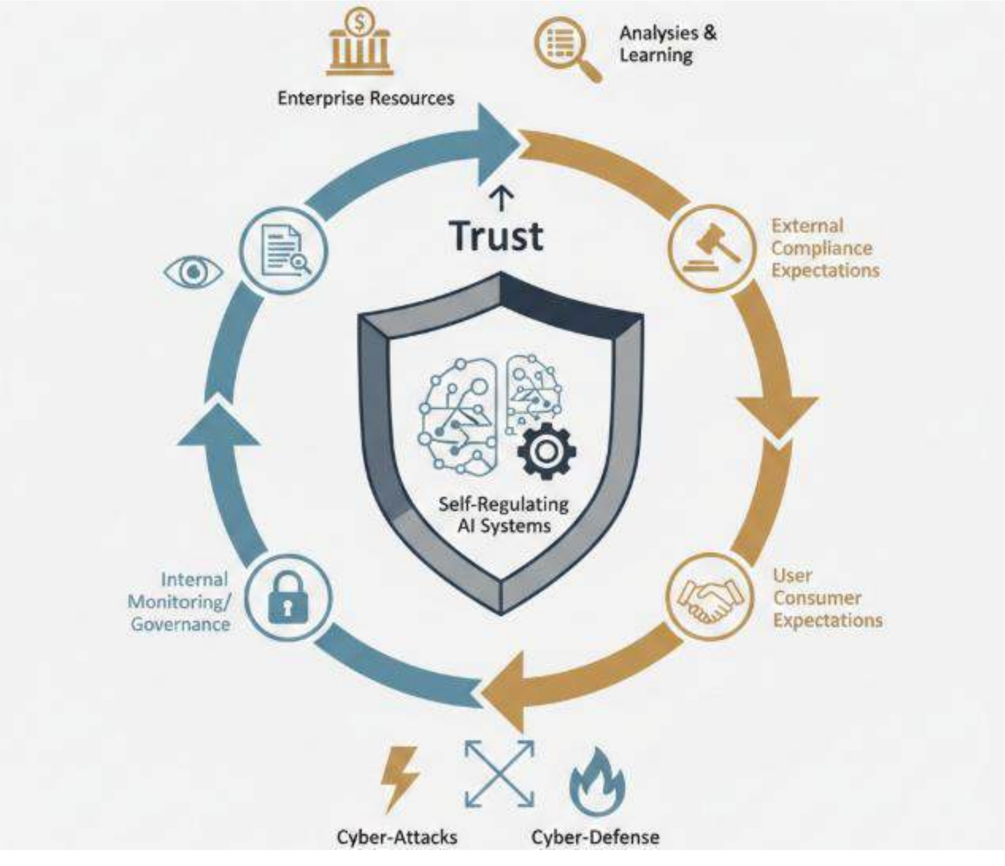
Enterprise Resources
Analysies & Learning
Trust
External Compliance Expectations
Self-Regulating AI Systems
User Consumer Expectations
Internal Monitoring/ Governance
Cyber-Attacks
Cyber-Defense

Fig 10.1: Bridging Autonomous Agency and Enterprise Governance: A Framework for Self-Regulating Trust in Intelligence Systems

Developing new systems is only one half of the equation; because autonomous decision-support systems will respond automatically to their environment, they will need to be able to adapt controls without human intervention or continual human monitoring. Even if internal monitoring is robust, it will need regulation—because of a strict governance environment, because such monitoring is expensive for the organization, or simply because the organization believes it is the right thing to do. These mechanisms must therefore be represented automatically in a manner commensurate with the organization's own capabilities and decision-making policies. The section therefore seeks to articulate the internal governance and external compliance requirements of enterprise intelligence systems, gathering questions that will support the bridging of self-regulation across levels of decision support and decision making as enterprise users and consumers demand greater visibility and control over such systems. In summary, business executives and enterprise intelligence technology users expect AI-driven enterprise intelligence systems to comply with external legal and regulatory requirements as well as internal governance frameworks.

10.2. Foundations of Trust and Self-Regulation in Enterprise Intelligence

Trust and self-regulation are especially important for enterprise intelligence systems, given their critical roles, interacting with delicate data and making consequential predictions and prescriptions in unpredictable environments. Understanding trust in these contexts must start with the foundations, the requisite elements and mechanisms that guide the design, architecture, and operation of a trustworthy system.

These elements can be viewed from within an enterprise, where the intelligence system is in a supporting role, or from outside, where the system is the source for decision-making and action, including implementation. In both cases, the system must demonstrate reliability in meeting its objectives and anticipated performance indicators, safety in causing no unexpected, uncontrolled harm and fulfilling any safety constraints, and transparency through sufficient explanations for the decisions and predictions made as to support an informed assessment of the intelligence's accountability. Such accountability assures that when trust is breached, the wrongdoing can be traced back to the responsible agent to enable redress and recovery.

10.2.1. Conceptual underpinnings of trust in AI systems

Faith in AI systems can be established through their consistent dependability and responsible conduct. Therefore, it is vital to ensure their reliability and safety, as well as to present reliable information about their inner workings and actions, complete with justifications. While a wealth of techniques exists for demonstrating or enhancing reliability and safety in the AI literature, clear definitions of safety and explainability have yet to gain widespread acceptance. The analysis presented here emphasizes the characteristics within these two areas that build trust.

AI systems must operate reliably within accepted capability limits. Conflict during execution can indicate a defect in either the AI agent or the operational environment. The two-pronged approach involves workflows that guarantee a trusted operational environment, complemented by triggers for policy recalibration, control-setting automation, and pre-emptive adaptation. Such adaptations adjust AI behaviour to mitigate hazard emergence, thus extending reliable operation under previously accepted policy settings. Trust in AI depends not only on the comprehensive coverage of reliable, safe operation, but also on continuous policy calibration to assure desired behaviour and risk management.

10.2.2. Self-regulation mechanisms: governance, control, and accountability

Emerging and trusted enterprise intelligence systems should incorporate self-regulation mechanisms by defining the necessary governance structure and configuring supporting control systems, including the roles and responsibilities of business, IT and supporting functions such as data, security and risk management. In addition, care should be taken to identify, define, calibrate and balance the full range of controls considered necessary. Responsibilities for controls typically assigned to users, IT, security, audit, risk and other groups should be determined from a data-centric perspective that is appropriate for the banks' business and risk profile.

The definition, entrenchment, jurisdiction, effectiveness and fitness-for-purpose of such controls should be regularly checked and updated. Self-regulation aims for policies that shape, mitigate and manage risk rather than simply preventing it. A useful starting point is the classification of controls as preventive, detective and corrective, with further subdivision into active (prompting, intervening and stopping), enabling (automating and assisting), and monitoring (auditing and signalling). These definitions include real-time but exclude post-mortem checks such as audit trails and audit tests.

10.3. Architectural Imperatives for Trustworthy Systems

Provenance, lineage, and data quality assurance are prerequisites for trust in AI systems. Provenance encodes the processes that have generated data through, for example, data coming from particular sensors, having certain configurations, or having been gathered at particular times or under particular conditions. Lineage records 'where did the data come from' and capture further dependencies with third parties. Provenance is foundational to assessing reliability, safety, and accountability because the users of AI systems need to understand which conditions must hold for the data to be considered reliable. Both provenance and lineage enable users to assess whether the quality dimensions relevant to their task are satisfied. Lineage allows expressing the dependencies of data quality metrics, such as completeness, accuracy, or consistency.

Quality assurance expresses how the dimensions of data quality are monitored in practice. Monitoring typically requires checks of the actual data against acceptable values, patterns, or distributions. These checks are then formalized as tests, which return either the result ('passed') or a doubt ('not passed'). Automated testing can, therefore, be seen as the monitoring function for data quality. Generalizing this approach leads to the notion of quality verification, which includes manual checks when abnormal situations arise. A verification act can thus require additional humans in the loop or may be triggered by unusual configurations. In summary, data quality assurance consists of defining the quality dimensions relevant for data provenance, creating quality tests for the current data, and using them in the verification process.

Transparency and explainability support trust by providing the appropriate insights at the right level of detail to the right users. Designing the disclosure of AI systems requires identifying the types of explanation needed, the users that require them, the level of abstraction or detail that is useful for each user, and any privacy considerations that may limit what information can be shared. Explanations can assume many forms, such as local or global, and there may be several levels of detail for each of them. Care must be taken in defining the levels of detail revealed because too little or too much information diminishes user trust. Furthermore, although it may be tempting to expose everything produced by the model explanation subsystem, sometimes it is better not to expose certain aspects because doing so may lead to a loss of trust.

10.3.1. Data provenance, lineage, and quality Assurance

Future Directions in Trusted and Self-Regulating Enterprise Intelligence Systems: Maintain an academic tone, present evidence-based arguments, and structure logically; prioritize clarity and formal articulation.

Trustworthy enterprise intelligence systems require data provenance, lineage, and quality assurance, which ensure that the data being used for analytics is the desired data. The importance of data is underscored by the adage "garbage in, garbage out." All intelligent or automated decisions are derived from data, and even the best algorithm will produce dubious outputs if the data being used is erroneous or biased. However, the advent of sources such as crowdsourced data, social media, Internet of Things-enabled sensor data, and data produced on demand using web scraping and other techniques means that it is vital to establish whether the data is safe and reliable prior to usage.

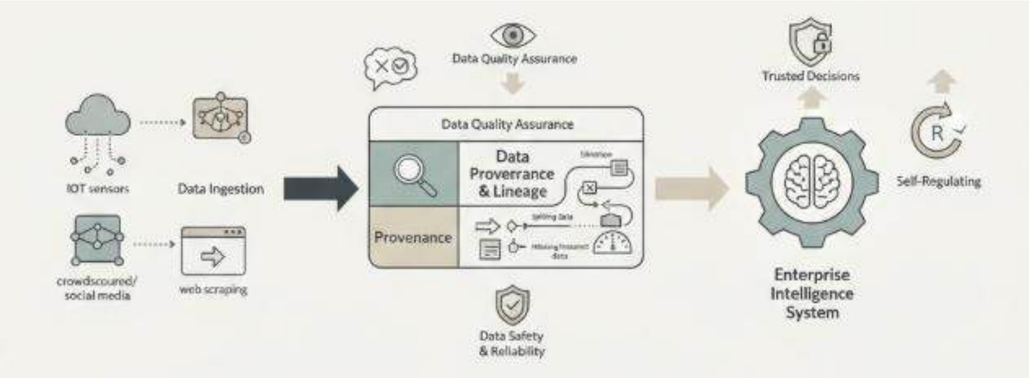

Fig 10.2: Architecting Trust: A Provenance-Centric Framework for Data Lineage and Quality Assurance in Enterprise Intelligence Systems

Data provenance and lineage tracking both seek to answer the question of where data comes from, but from different perspectives. Data provenance traces the original sources and origins of the data, while data lineage studies the life cycle of data over time, identifying its flow from source to destination. Data lineage has thus-evolved into a broader concept, embracing various aspects such as dismissing or splitting data; changing schema, format, or granularity; data fusion through joins and association rules; missing or incorrect data; and data quality. A typical data lineage metric would quantify the number of lineage paths leading to a data object.

10.3.2. Transparency, explainability, and user-aligned disclosure

The usefulness of a computational system's decision-making mechanism is not only a question of system performance, but also a consideration of how the mechanism is represented to the user. Transparency emphasizes making the process of decision- and action-support comprehensible for users—a requisite for them to understand and trust the findings. Explainability refers to mechanisms that make it possible for a user or stakeholder to comprehend the essential decision-making components of an algorithmic system. There are many ways to achieve these goals, including relying on inherently interpretable methods (like decision trees) for the outputting of algorithms, or the provision of additional, dedicated, explainer systems.

Existing models for transparency and explainability developed for machine learning can serve as initial building blocks for enterprise intelligence systems, but they need to be expanded and tailored in various ways. First, because enterprise intelligence systems often deploy multiple competing black-box reasoning models, it is insufficient for the explanation to focus on a single analysis; it must explain all of the models, their relative confidence, and how trust in each model can change over time. Second, users are rarely acting alone; a more nuanced view of transparency must consider the network of compute nodes, which are either computing resources or groups of individuals, that built the data and processes that form the basis of their trust in model outputs. Consequently, users have distinct profiles that require different levels of explanation detail and focus.

Finally, it is important to clarify that striving for transparency and explainability is inherently a trade-off with performance. During a machine-learning project, decisions must therefore be made about what goal to prioritize at each stage or component while still satisfying the users' fundamental need to trust the output. Rather than attempting to optimally satisfy every user on each occasion, it is often more productive to map users into transparent-explainable models, or parallel structures, within the overall system.

10.4. Governance, Compliance, and Ethical Frameworks

Legal and Regulatory Alignment in Enterprise Contexts

In corporate and industrial contexts, intelligence systems must be sensitive to specific laws and regulations that govern activities such as consumer protection, data stewardship, employment, taxes, trade secrets, and more. For example, Special Purpose Acquisition Companies (SPACs) in the United States are subject to additional disclosure requirements. Understanding the legal landscape that applies to an enterprise or industrial sector is a critical first step. Business, legal, and technical staff must identify the legal, regulatory, and contractual framework that guides their organization's operations. Formulating a comprehensive checklist of applicable laws, standards, and governance rituals helps teams determine transparency and compliance demands for intelligence systems.

Consider the implications of the Consumer Product Safety Improvement Act of 2008 (CPSIA) on predictive and prescriptive analytics systems used to launch or revamp a product line for children under 13 years of age. These systems are expected to contain recommendations on factors such as pricing, features, delivery, and modes of distribution. Enterprises need to create operational statements for these systems or control artifacts that confirm the systems have the required features and fulfill the CPSIA statement. Subsequent reviews must ensure these statements remain up-to-date and validated. These considerations also apply to enterprise risk management systems. When significant changes are made, compliance workflows trace how the risk management system's analysis and predictions have been affected. Consistent with SOX, the electronic records of analysis findings, confirmations of the flow statements, and attribution of contributions must also be archived.

Ethical Guidelines, Bias Mitigation, and Fairness

Most corporate and industrial intelligence systems remain unmonitored from an ethical perspective. Ethical guidelines, corporate policies, and an organization's culture must be codified to guide the stakeholders that influence these systems. These codifications articulate expected behavior and the factors that make such behavior desirable and provide sufficient concepts and tools to recognize, assess, and fix unethical behavior should it occur. For instance, the code of ethics for a bank defines integrity and provides guidance on detecting and resisting bribery. This allows the Truthful Judgment and Action Model, which predicts likely behaviors of different stakeholders, to identify when integrity is not being honored. These codes formally address the fairness of intelligence systems.

Analytics systems applied to policies that contain demographic data must be checked not just for valid performance but also for bias in sensitive groups. Bias may be introduced into prediction systems either because a bias from the past is propagated into the future or because an outcome not warranted by facts is favored or penalized for specific groups based on gender, religion, or race. The software used to audit for bias employs counterfactual fairness tests.

10.4.1. Legal and regulatory alignment in enterprise contexts

Enterprise decision-makers face myriad civic, fiscal, and criminal compliance obligations while concurrently pursuing self-service and asset-collaborative intelligence agility. The necessity of preserving customer data uses not only the organization but the individuals themselves places enterprises under pressure to select only winning policies and avail of revenue opportunities to customers while having no control of their data when it is shared with providers. Harmonizing regulatory and governance coordination across jurisdictions facilitates compliance with all applicable laws and domain standards such as the BDAR. The laws and standards addressed require selected types of evidence and execution patterns while audited rituals drive legal defensibility and compliance certification. Trust is the foundation that supports compliance; compliance is the foundation on which enterprise intelligence and architectures operate.

Legal assurances for AI systems and their governance in enterprise contexts are mapped against existing laws, regulatory obligations, and standards. Workflows enable, verify, and assure compliance with legal and regulation standards for data governance and enterprise intelligence.

10.4.2. Ethical guidelines, bias mitigation, and fairness

Privacy and civil rights represent fundamental assets of society. Consequently, voice bias, algorithmic bias, and data ownership, sharing, and stewardship have received substantial media, industry, and regulatory attention. Yet, historically, such sensitivity arises much later than the actual practice in the field. Therefore, the presence of trust-related and ethical alignment mechanisms in organisations is regarded as a wish list and long-term aspiration rather than a business reality.

1. Voice Bias.

Voice bias stems not from the analytical algorithms but from data—represented users' voices—and underlying issues. The training of speech analytics models requires genuinely diverse user voices; otherwise, the model performance is compromised. Hence, analytic models have to be trained, tested, and validated with respect to characteristics that may distort the meaning of voice. If a particular shape of voice is under-represented, understandable misclassifications are inevitable. In the best-case scenario, these are harmless; in the worst case, they could have disastrous consequences in highly regulated industries (e.g., defence, health). An external independent party can assess the above aspects for organisations and alert when the risk of voice bias is increasingly present. When using third-party models, organisations could ask (but not require) that model providers disclose the data characteristics used for analysis. Therefore, potential clients can evaluate model performance risk with regard to their user base.

2. Algorithmic Bias and Autonomy-Enabled Techniques.

Algorithmic bias implies inaccuracies that are closely correlated with sensitive attributes of affected customers. There are several commercial tools for measuring model bias, and such biases are common. In addition to external checks during model training, self-regulation of bias could be implemented for recently deployed models that need to adapt continuously. Adjustments could happen at the task level or across multiple tasks. Risky groups are constantly monitored, and when their derived outcomes present critical biases that are above specific limits, remedial actions are automatically proposed using previous examples. When the problem persists, an external governing body highlights the risk. An additional option could automatically block algorithmic decision-making in such cases until the algorithm adapts successfully.

10.5. Self-Regulation Mechanisms in Practice

Enterprise analytics systems must demonstrate the ability to self-regulate through automated techniques and procedures. Examples are found in the areas of autonomous policy evolution and risk management, self-checks for sensitive operations, model monitoring, and anomaly detection.

Enterprise analytics systems may autonomously evolve their operating policies based on a self-defined process. This may include automated provisioning of the analytic model environment by construction or adaptation techniques, using the deprovisioning and validation processes as checkpoints. Internal self-risk-models may trigger a self-request for provisioning updates. Characteristics that are subject to risk-based triggering must be defined and continuously assessed trends. Disqualification criteria may prevent accidental initiation of policy adaptation in a changed environment, using trend-curve characteristics not suitable for the model at that time. In such cases the operating policy may remain in use until an opportunity emerges for replenishment with a checked policy update. Rollover during adaptation must also be possible.

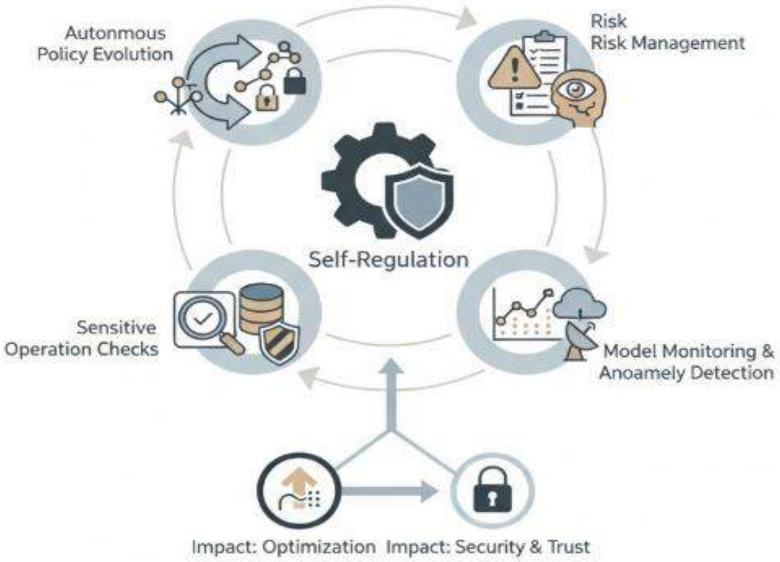

Fig 10.3: Autonomous Governance Frameworks: Self-Regulating Protocols for Enterprise Analytic Ecosystems

Enterprise systems may perform automatic checks for sensitive operations as they approach execution. Each detected operation can trigger a check that verifies if it is under conditions of a pre-defined check-list related to vulnerability. The check-list may cover risks such as abnormal costs, privacy issues due to massive linking of known public data sources, the presence of a turbulent algorithm or a juvenile model at that stage of life. Enterprise analytics systems can implement monitoring of model-latent characteristics, related environments and operational contexts.

10.5.1. Autonomous policy adaptation and risk management

Policies governing intelligent agents that act autonomously are rarely observed to change; yet the world constantly evolves. These agents need to dynamically adapt in order to steer clear of new pitfalls and safely explore new opportunities for value creation. Policy evolution is most naturally accomplished with the help of calibration controls that periodically and simultaneously adjust multiple aspects of these policies, such as risk appetite, degree of exploration in robot learning, and thresholds for triggering alerts to supervisors and stakeholders. In some cases, agent safety provides a signal for a change in risk appetite. In others, when the safety and compliance signals enter the red zone, bold exploration can be prudently curtailed. Keeping the flush zone sufficiently broad occasionally allows proactive increases in risk appetite. Fully automatic calibration of risk appetite and associated knob settings comes with dangers, especially the potential menace of unprovoked catastrophic failure. When the accident-prone region is based on an event that has not previously occurred, the calibration control cannot be trained to prevent recurrence. An evolving policy also needs to be periodically validated and can be rolled back on detection of dangerous side effects that are not properly handled by backup safety and compliance mechanisms.

Auto-pilots have a built-in terminal that warns pilots about unsafe flying conditions of which they may be unaware. Humans can respond either to the warning or to the underlying cause of the danger, such as potential engine failure. Pilots are, of course, requested to maintain visual contact with the flying machine. The designed complexity inherent with all trusted intelligent autonomous agents is that there are multiple agents whose behaviour needs to be studied, monitored and managed at the same time.

10.5.2. Self-checks, model monitoring, and anomaly detection

Policy adaptation and tuning in real-world settings frequently require expert time and skills. Continuous improvement loops embedded within enterprise systems can initiate feedback and adaptation in a variety of indirect ways. Self-checks validate the outputs of predictive models in order to identify when the models may be producing unsuitable results and should therefore be switched off. Model monitoring analyzes the statistical characteristics of the outputs as well as available inputs and raises alarms when thresholds are breached. Anomaly detection applies domain knowledge to detect unexpected results, such as stock-market changes beyond certain levels.

Self-checks compare a predictive model's output to parallel estimates generated by relatively simple approaches or business rules. Self-checks protect against errors and, in the event of anomalies, can provide direction to domain experts for rapid investigation and resolution. Analysis of a variety of self-checks supports the conclusion that the majority indeed operate as useful flags rather than nonsensical or useless alerts. A normative model of self-check functioning identifies key setup considerations: reliability of self-checks, actor clarity regarding normal ranges, and action-planning based on their rare, coherent, and consequential alerts.

10.6. Data Stewardship and Security by Design

Enterprise intelligence and analytics systems routinely operate on sensitive and proprietary data. Protecting individuals' privacy and organizations' confidentiality when deriving knowledge from cross-organizational data is hence crucial. Individuals whose data are consumed should feel comfortable with their privacy being safeguarded and that they would not be harmed in case they disclose their information to multiple organizations. Organizations should consider the risk of disclosing too much of their information, because from revealing too much data they may unintentionally indirectly disclose information that is of strategic nature for their business through data analytics and especially through machine learning.

Federated Learning enables organizations processing highly sensitive data to mutually exploit their individual information, avoiding exposing the raw data themselves to each other. Privacy-preserving techniques, for preserving individuals' anonymity and confidentiality, can introduce overhead in terms of performance, implementation complexity or disclosure risk. Proper information governance and control models for external analytic systems are employed to provide the adequate level of privacy-preservation to foster individuals' and organizations' trust in these cross-organizational analytics systems.

10.6.1. Federated and privacy-preserving analytics

Federated Learning (FL) provides a decentralized approach to analytic model training and emulation of Distributed Machine Learning (ML) models, designed explicitly for cross-organizational data sharing. FL's primary advantage lies in the requirement that only weights need to be exchanged among organizations explicitly mapping the ML model across organizations aiming to train a better model. Therefore, organizations avoid sharing local raw data, ensuring local data privacy by design. The FL process can also be adapted for low-cost Local Differential Privacy (LDP) with automatic noise addition; however, the architecture should support the centralized noise management to guarantee the privacy budget is met.

Federated Knowledge Graph Completion utilizes the federated environment for the knowledge graph completion task. It decomposes the task into subproblems, distributes them to different clients with the respective local knowledge graphs, and integrates the completion results to enhance the global knowledge graph without revealing local private knowledge graphs. FL methods should also be combined with secure multi-party computation or homomorphic encryption approaches, allowing organizations to jointly develop ML models without direct access to each other's datasets while ensuring local data confidentiality.

10.6.2. Secure data governance and access control

Comprehensive security-by-design policies must be enacted for AI systems throughout the various stages of their life cycles, beginning with project initiation and prioritizing data responsibilities from the outset. Thus, an enterprise may wish to adopt a complete access control model that ensures all data, and particularly sensitive datasets, are encrypted (in active and at-rest states) with keys that it never possesses or owns. This may be supplemented by the introduction of other techniques underlying access control for the data used within AI systems, e.g., cryptographic access control mechanisms that accomplish independent encryption of each record inside the dataset using different keys encrypted separately. Such protocols permit auditing capabilities and impose the minimization principle, ensuring only the parties who need access to a sensitive record will hold the key towards decrypting it.

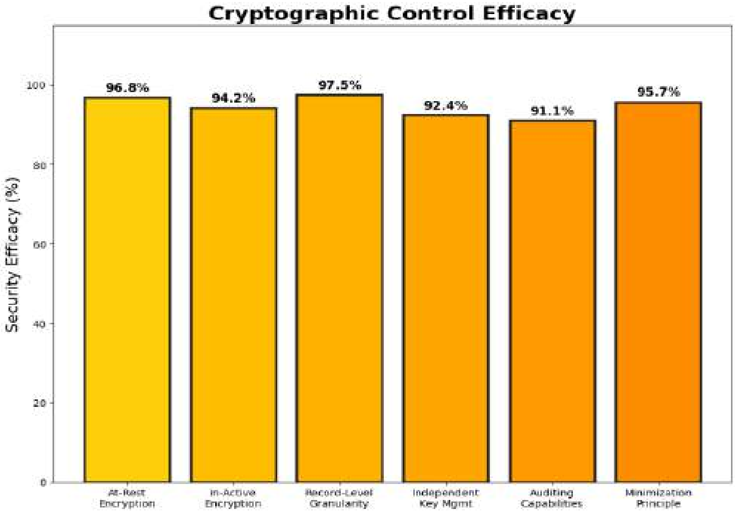

Fig 10.4: Cryptographic Control Efficacy

Data governance guidelines require the definition of access-control mechanisms that guarantee each instance of the intelligence system has access to the data it absolutely requires, without being able to gain knowledge on data that is not related to its functionalities. Access must logically be granted according to user profiles, with independent data encryption for each class of users. Heterogeneity among organizations may also span data formats and AI models, importantly affecting the enterprise's predictive accuracy. Approaches enabling federated and privacy-preserving analytics offer solutions to address such issues by permitting cross-organizational data analysis while still delivering privacy guarantees.

10.7. Conclusion

Building trusted enterprise intelligence systems—enabling organizations to act on timely, accurate information, operate autonomously, and adapt policy and behavior through self-checks, self-optimizing, and self-regulating capabilities—requires architectural and design choices at the micro and macro levels. These choices support the properties of enterprise intelligence systems that assure the reliability, safety, transparency, and auditability requisite for human-level trust.

Among the imperative choices are ensuring data provenance, quality, and core principles of transparency and explainability; aligning enterprise-specific elements with external governance by laws, regulations, and compliance rituals; addressing bias, fairness, and privacy; and implementing automated, federated, privacy-preserving analytics models. Strategies and procedures for adapting operations, policies, and rules in response to risks; for continuous monitoring of core operation models and detection of anomalies in their outputs; and for detecting model drift and adapting superseding models are also fundamental. While many of these mechanisms are well understood in isolation, demonstration of self-regulation, and the guarantees or assurances that stem from it, remain open research questions. Research directions are thus suggested, together with sets of architectural choices and engineering considerations that illustrate directions toward realisation in building trusted and self-regulating enterprise-intelligent systems.

10.7.1. Final Reflections on Building Trustworthy Enterprise Intelligence Systems

Building Trusted and Self-Regulating Enterprise Intelligence Systems: Final Reflections

Undoubtedly, trust and self-regulatory capabilities are fundamental prerequisites for the development and effective deployment of enterprise intelligence systems. Fulfilling the various requirements that would trigger and sustain user trust in the intelligent system's operations is, however, a complex challenge, given the multitude of aspects that have to be considered. These result mainly from the reliance on systems that integrate traditional and modern AI techniques whilst operating in intricate enterprise environments.

Therefore, the concept of enterprise intelligence goes beyond the capability to achieve an accurate prediction. It encompasses the need to provide the necessary explanation to all relevant stakeholders, to comply with applicable laws, regulations, standards, or ethical norms, and to allow for audits and re-validations whenever unforeseen changes arise in the intelligent system's operating context. Addressing these requirements is essential in enabling enterprise intelligence systems to evolve from an auxiliary business tool to an essential backbone that would steer the enterprise's long-term performance. Therefore, additional research work is required to refine self-regulation mechanisms further. Additional self-checking mechanisms capable of triggering an automatic return to a policy that is known to work are also needed, as are systems that watch for model failure or malfunction and relay the information, so that an investigation can be begun, possibly before actual failure or malfunction.

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