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Chapter 10: Future Directions in Autonomous and Self-Optimizing Enterprise Systems

10.1. Introduction

Autonomy enables enterprises to react to their environments without human intervention. The race to become autonomous is driven by large investments in remote sensing, AI-enabled decision-making, and robotic hardware. Although true autonomy has not been achieved, core capabilities are being developed and demonstrated in industry. Traditional enterprise resource planning (ERP) systems and business process automation, although important, function as reflexes in response to human impulses and decisions. Advances in AIS, applied AI, and autonomous systems suggest that future enterprise systems may no longer rely on humans to sense, reason, and act in all but the most extreme situations. Such systems could be termed autonomous, a definition that encompasses but is not limited to the commonly used term self-driving or self-riding.

Autonomous systems differ from human-driven systems in that the environment's dynamics are either known or can be accurately modeled, allowing the system to operate with little or no human involvement. Self-optimizing systems, on the other hand, are designed to improve their performance by detecting and responding to changes within their environments. A self-optimizing system can be thought of as a closed-loop feedback system for any enterprise function, with the controller often taking the form of an AIS that implements a standard optimization solution for a well-defined performance objective. Although autonomous execution cannot be achieved for all enterprise tasks, there is an opportunity to define a narrower long tail of enterprise execution that leverages human involvement simply when required.

10.1.1. Background and Significance

The concept of autonomy in enterprise systems has been a recurring theme for many years but is now gaining traction due to key Enabling Technologies such as Cloud

Computing, Artificial Intelligence, Autonomous Agents, and the Internet of Things (IoT). Automation has long been a goal of enterprise systems, and while major strides have been made in automating large chunks of enterprise operation—particularly back-office processes—less attention has been given to semi-autonomous operation of a wider area of enterprise functions, now often referred to as Self-Optimizing Enterprises. This extends into optimizing across Supply Chain networks and into real-time detection of risk and fraud.

Three specific lenses can help articulate the characteristics, benefits, and concerns of this approach to enterprise systems: (1) the Autonomous Enterprise supply chain networked paradigm; (2) the detection of problems within the finance function—unregulated near-autonomously by financial institutions; and (3) the magnification of risk within the enterprise through the use of Artificial Intelligence (AI), particularly Machine Learning methods. Traditionally, risks and detection of problems within financial functions were anticipated and made explicit through Control Frameworks. However, these functions are becoming fragmented and near-autonomous and require the magnifying lens of risk detection by the enterprise—much like internal audit functions.

Fig 10.1: Future Directions in Autonomous and Self-Optimizing Enterprise Systems

10.1.2. Research design

A mixed-methods study design combines empirical investigations in specific enterprise functions with a comprehensive literature review. The forensic analysis of a sales

transaction exploits accessible transaction logs and accommodate pre-definable behavioural variables. The validation of enterprise-wide transparency employs extant data from Meta and is made possible through a newly developed taxonomy of multi-modal transparency.

The majority of the research published to date either adopts an empirical approach—aiming to identify and describe the early instances of autonomous and self-optimizing enterprise systems—or develops individual building blocks for a holistic system. These contributions provide individual enablers in designated domains while leaving the analysis and specification of their interactions only partly complete. It is, therefore, of value to distil from the literature all the presently known building blocks together with their interdependencies and their relationships in the broader context of enterprise information systems (EIS). The resulting framework represents an ex-ante validation of the importance and demonstrable benefits of the autonomous and self-optimizing paradigm and serve as a guide for further detailed investigations. The resulting multicriteria assessment examines whether, when, and why the implementation of autonomous and self-optimizing units of analysis enhances the traditional factors of efficiency, effectiveness, and economic viability.

10.2. Foundations of Autonomous Enterprise Systems

Both sensory devices and perception pipelines have advanced tremendously over the years. Sensing systems based on a multitude of modalities (e.g., cameras, radar, infrared, LiDAR) provide data on various aspects of the environment. Perception pipelines combine these modalities to achieve situational awareness, although specific pipelines may still be used for different tasks. In addition to object detection, recognition, and distance measurement, these pipelines provide higher-level information such as free-space mapping or semantic segmentation. Natural language processing systems can handle unstructured text input and are increasingly being integrated into multimodal systems. Reasoning architectures that combine classical planning and deep reinforcement learning into a hybrid approach are becoming popular, along with decision cycles that fuse model-based and model-free methods. All of these capabilities are paving the way toward real-time controlling of industrial systems.

Low latency is an important attribute of sensor-actuator loops; safety requirements impose further constraints on sensing and action times; and systems must be robust against actuator, sensor, and communication failures when deployed in real-world environments. These advances are now enabling blurring system borders and granting agencies improved autonomy through more sophisticated sensing, reasoning, and acting capabilities.

10.2.1. Sensing, Reasoning, and Acting in Dynamic Environments

Autonomy in enterprises has evolved from limited rule-based automation towards adaptive self-organization and has recently progressed to fully autonomous self-optimizing systems. A wider range of enabling technologies are now available, and in combination, they allow enterprise systems to interact with dynamic environments in open-loop-free and closed-loop ways, with increasing levels of reliability and safety. Enterprises endowed with these capabilities can achieve significant competitive advantage by providing consistent, high-quality value to customers at the lowest possible cost. As a result, the ability to operate autonomously becomes the standard for a growing number of enterprise functions. Nevertheless, to safeguard stakeholders from potential exploitation, strong supervision, monitoring, and independent auditing are needed.

Across all enterprise functions, autonomous systems perceive their environments, reason about the current situation, and act either independently or in collaboration with humans and machines. Sensing encompasses detection and estimation, with activities such as gathering information and inferring customer needs representing perception. Reasoning includes both decision-making and planning, while acting includes operational control, teamwork, and communication. These three categories form the core of all intelligent autonomous systems, although not all autonomous systems require all aspects.

10.2.2. Self-Optimization: Feedback Loops and Objective Alignment

Self-optimization is required for enterprises to reach their full potential, enabling nimble alignment with constantly changing conditions and stakeholder needs without the need for constant external steering. For real-world enterprise systems to approach true self-optimization, the design and tuning of critical feedback loops need to be approached holistically. The qualities and placement of key objective functions determine whether stability and convergence in desired directions are achieved.

In practice, the definition of objective functions, their alignment with organizational performance, and the resolution of conflicts among them present major challenges during self-optimization. Organizations usually explore the solution space of feedback loops for a restricted set of environmental conditions that are then assumed to persist. Their designs for self-optimizing feedback loops break down when conflicting objectives appear, as they so often do. The subjective and unquantified nature of such assessments introduces the real danger of overlooking critical constraints. Emphasis on short-term optimization for any one objective often leads to degradation in other areas even when these are explicitly modeled. For genuine self-optimization, objective functions need to be defined, mapped, and updated seamlessly across internal and

external enterprise functions. Convergence in the desired direction must therefore be ultimately prioritized over the degree of convergence along any single dimension.

10.3. Architectural Paradigms for Autonomy

Two architectural paradigms emerge in the context of autonomy, particularly driven by the requirements of sensing, reasoning, and acting in dynamic environments. The first paradigm is a modular microservices ecosystem that employs a coordinating control plane without enforcing a centralized orchestrator. This design promotes composability, autonomy, and scalability, while enhancing observability and fault isolation during execution. The second paradigm consists of a data fabric that enables seamless interaction with the required information, thereby facilitating the earlier mentioned Enterprise Sensing Roadmap (ESR). The ESR serves as the improved Enterprise Information System (EIS) for enterprise resource planning (ERP) systems of the next generation.

Fig 10.2: Architectural Paradigms for Autonomy

The key enabler of the modular microservices ecosystem is a microservices architecture at an optimal grain size. The microservice design should foster sufficient composability and observability of permutations and combinations of service execution, while the combination of coordination, control, and orchestration serves to ensure the fulfillment of all assembly requirements, thereby assuring the reliability and quality of the execution even during the analysis of failure modes or other corner cases. Furthermore, the

deployment of an autonomous enterprise involves an ecosystem of microservice providers, and hence operational security is of particular concern, especially when critical services are provided and courted.

10.3.1. Modular Microservices and Orchestration

Autonomous and self-optimizing enterprise systems will increasingly rely on microservice architectures, with modular decomposition and service granularity tailored for specific applications. Such a design promotes observability, fault isolation, and independent evolution while also introducing new challenges. Composability, scaling, and security must be carefully governed; resilience and performance still depend on orchestration, enabling control across multiple services. Autonomy and self-optimization at the enterprise level may be better achieved through cloud-native microservice and orchestration ecosystems.

The operational risks of excessively complex and monolithic ERP solutions have renewed interest in more modular approaches. Microservices and service meshes enable a higher-degree-of-freedom design for large and complex systems, with services evolved, deployed, and scaled independently. Within the enterprise context, achieving composability and observability is critical: composability facilitates rapid configuration and adaptation, while observability supports diagnosis and failure recovery. Changes in policies, objectives, and regulations can lead to the idleing, removal, or configuration of services that no longer meet business needs.

10.3.2. Data Fabric, Quality, and Provenance

A data fabric integrates enterprise data from multiple sources to deliver consistent, contextualized information across users and applications. Stakeholders require comprehensive understanding of data lineage that includes both provenance—information on how a particular data product was produced—and semantic metadata that describes the meaning and significance of attributes. Data must be fit for purpose in terms of quality (accuracy, completeness, consistency, timeliness) and integrity (protection from corruption). Although enterprise functions implement data catalogues and quality systems, lack of common mechanisms leads to redundancy.

Autonomous systems gather and analyze data from suppliers, customers, and the environment for broad situational awareness. Quality and provenance are particularly crucial for those processes using machine learning—algorithm-driven decisions are only as good as the training datasets. Transactions involving automated agents require

rigorous integrity controls to prevent attacks. These elements must be implemented with considerations for user access rights, legal obligations, and data sharing regulations.

10.4. Methods for Self-Optimization

Self-optimization can encompass various methods that update an enterprise system continuously and automatically. The two principal classes currently explored in effect are policy-based control methods, including reinforcement learning, and auto-tuning or meta-learning techniques that alter internal parameters.

Policy-based Control and Reinforcement Learning

Policy-based control methods optimize a feedback-loop controller via a separate meta-optimization process. The design of the control problem is generally expressed using structured choices for a reward function, state representation, action space, and safety constraints. Policy frameworks use some representation suited to the application and selection of candidate-control policies can incorporate task structure for sample efficiency. A challenging aspect is finding an effective balance between exploration and exploitation. Model-based methods that learn a model of the dynamic environment offer the possibility of less sample-efficient planning, but are more difficult to engineer and can still suffer from issues when the model is inaccurate.

Auto-Tuning, Meta-Learning, and Continuous Improvement

Auto-tuning approaches provide for the continuous or periodic optimization of a configurable component and are particularly useful in deployment scenarios where a one-time tuning is insufficient or impractical. Such tuning can include the hyperparameter optimization practiced in supervised learning and the continuous adjustment of supply-chain parameters such as inventory levels. Meta-learning strategies that can formalize the main effect of extra training-time consider that the extra computation at deployment need only be a small fraction of the main task and ultimately lead to faster learning.

10.4.1. Policy-Based Control and Reinforcement Learning

Policy-Based Control and Reinforcement Learning

Policy-based control approaches, which determine how an enterprise system should act in a given situation, allow for both high-level and detailed control. The policies can be either handcrafted or learned through experience. Feedback from the environment is generally provided in the form of rewards, which is inherently a form of reinforcement learning. As control is based on interaction with the environment, policy-based

approaches typically require much data and an adequately realistic simulation model for safe training, but when available these approaches can learn efficient solutions. Exploration-exploitation trade-offs need to be managed carefully. In safety-critical applications, constraints on actions that could lead to catastrophic failures must be integrated into the learning process. If such constraints can be specified, a potentially large state-action space can be searched and reduced to an action space known to be safe. However, policy-based control mechanisms also add a new threat surface to the system. Malware or attackers that gain policies can manipulate the system, potentially leading to catastrophic consequences. Furthermore, if the policies are not change-resistant and can be adapted by attacking the tuning mechanism, the enterprise can become vulnerable to sudden shifts in the environment, such as changes in supply or demand.

Human experts typically express experience of what to do in challenging circumstances as heuristics or patterns, often in the form of "if X, then do Y." When an enterprise faces an unanticipated set of circumstances, heuristics cannot be freely adapted. Consequently, approaches that use machine learning to acquire new sets of heuristics that can be used for different circumstances or sets of actors are especially useful. Such learned heuristics are called meta-learned functions or algorithms. They speed up the process of identifying a suitable algorithm, speeding up the adaptation process. The sources of observed patterns can also be tracked to provide explanations of discrimination in decisions.

10.4.2. Auto-Tuning, Meta-Learning, and Continuous Improvement

An evolving business environment makes stepwise adaptation unfeasible. Consequently, and alongside decision automation, enterprises should also autonomously tune model parameters. For example, the identification of a time series model may be automated either through an empirical search (auto-tuning) or by leveraging previously explored models, experiences, and accumulated information on model structures (meta-learning).

To support continuous improvement of enterprise performance without traditional stepwise adaptation efforts, Humans+AI+Data systems should monitor process data and assist the HUMINT analyst with the establishment of improvement opportunities, such as process model mismatches and meta-model refinements. Potentially useful new data sources for the process, e.g., different data acquisition modalities, can be identified, assessed, and introduced. Additionally, evaluation mechanisms should be in place to allow for robust and controllable paths towards innovation but should still minimize inertia. Safety, rollback, and audit mechanisms should also be in place to introduce continuous improvement.

10.5. Applications Across Enterprise Functions

Although many enabling technologies are still in their infancy, autonomous or self-optimizing enterprise systems and their components are finding application across various enterprise functions.

In supply-chain and operations management, external circumstances, demand, and other inputs are increasingly sensed and incorporated into enterprise demand forecasts and production schedules, which are subsequently executed through business processes that largely require little or no manual involvement. Sensing, planning, and action mechanisms involved in demand sensing, autonomous planning, and autonomous execution are addressed. Some firms are also developing new resilience-related metrics that combine cost-to-service with service redundancy.

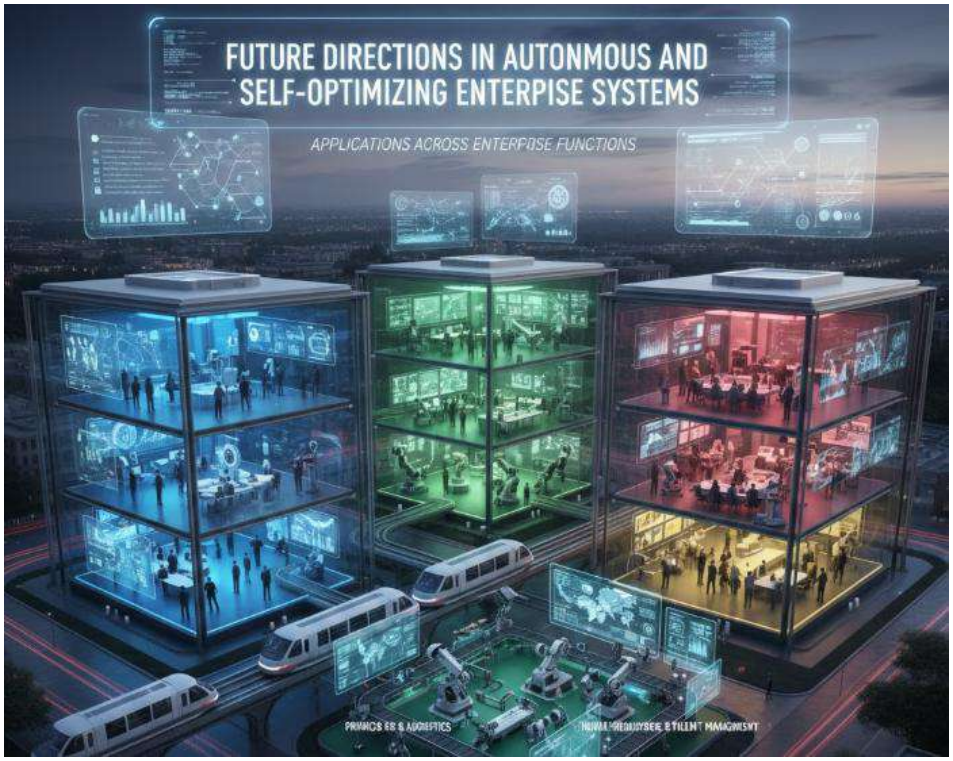

Fig 10.3: Applications Across Enterprise Functions

The finance, risk, and compliance functions are similarly advancing towards autonomy and self-optimization. Many enterprises are exploring the use of anomaly detection techniques to automatically identify fraudulent transactions; some are enabling robotic process automation solutions to manage these transactions continuously. An additional area of focus is the automatic execution of regulatory compliance requirements. Other enterprises are also deploying autonomous risk-function solutions that continuously

sense risk and dynamically adjust policies. Current research addresses risk, explainability, auditability, fragmentation, and the provision of control planes that guide these self-optimizing functions.

10.5.1. Supply Chain and Operations

Tenets of Autonomous Enterprise Systems; Self-Optimizing Biospheres; Supply Chain and Operations. Autonomous enterprise systems are capable of autonomous planning, supply-demand synchronization, autonomous support, and reasoning during execution. These techniques enhance resilience and service level improvement while minimizing overall operating costs.

New innovations in industrial control technologies will enable autonomous enterprise systems to self-optimize in harmony with organizational performance objectives across the complete supply chain. The adaptation of planning and control policies will also take place in an automated manner, significantly improving the cost-to-service ratio. Demand sensing will use complex internal and external signals to reveal immediate changes in purchasing patterns. The data will aid the automatic replenishment of stock and enhance the robustness of planning against unforeseen disturbances. External risk signals will be monitored in real time, and automatic corrections will be made to inventory policies, replenishment and sales plans, sourcing decisions, and transport operations.

The upward trend to a frictionless digital economy and the complexities and uncertainties of the globalized enterprise ecosystem pose ever-increasing challenges to position and operate. The emphasis is on preparation in bid-response delivery time, desire for minor errors, need for realism on cost, and wish for environmental responsibility. Allowing computers to undertake independent thought in planning and execution should be the ideal. Thus, automation has reached the level of managing itself in both steering and governance, a dimension of artificial intelligence that will gradually permeate configuration, execution, planning, analysis, and steering of services and products.

10.5.2. Finance, Risk, and Compliance

Finance is traditionally seen as a unit optimized for control with limited information-sharing, even an adversarial stance towards other functions. This view is being challenged by a new landscape in which AI is enabling rapid anomaly detection, facilitating regulatory compliance automation, and enhancing risk management strategies. Sophisticated enterprise systems, tailored for processing and distributing corporate financial information (including the generation of financial statements), might

evolve into an autonomous function capable of controlling and executing the complete set of transactional operations at greatly reduced costs while eliminating information asymmetries. Controls can be further strengthened by audit trails available as part of the normal use of the system.

The same technology that enables autonomous finance also facilitates a holistic view of risk management, from the generation and processing of financial statements to detection of internal and external threats. The level of explanation available via the enterprise system is expected to ensure regulatory acceptance of the associated decision-making (e.g., for surveillance purposes). At the same time, the operational technology for detection, and application, of effective mitigations is constantly improving.

10.6. Challenges and Risks

Enterprise Information Systems (EIS) increasingly rely on AI-based systems. While machine learning models are trained for optimal operation, sufficient attention is not paid to operation deployment and management. AI failures have significant financial implications, showcasing the need for continuous learning and improvement. Efforts to investigate potential design patterns are therefore critical. This paper focuses on the risks and challenges that AI-based systems pose in large organizations and why autonomous elements are critical.

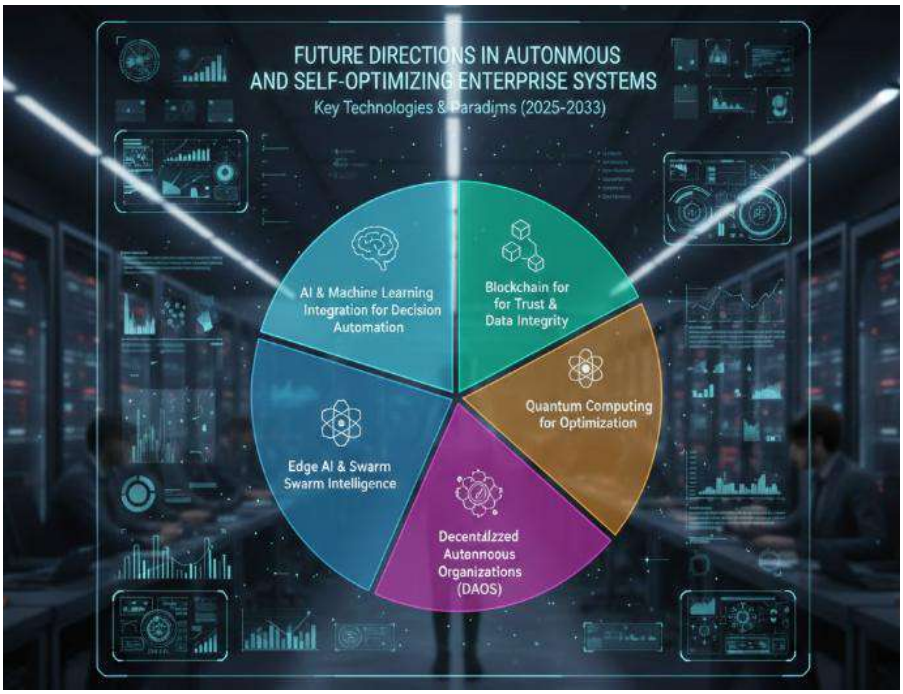

Fig 10.4: Future Directions in Autonomous and Self-Optimizing Enterprise Systems

Satisfying regulatory requirements while responding to AI-related audit requirements can place a significant burden on autonomous decision-making. Organizations need to ensure that AI technologies are trustworthy, explaining how data is obtained, how models were learned, and the business objectives of deployed AI technologies, whether undertaken through an eyes-off or eyes-on approach. Data can be used unethically, giving rise to data trust issues.

10.6.1. Data Privacy, Security, and Resilience

The Task Force considers data privacy and security in autonomous enterprise systems, which face increased vulnerability from expanded attack surfaces related to connectivity, decentralization, and multi-stakeholder collaboration. An operational risk framework for threat assessment and mitigation is proposed, supported by ethical guidelines for AI deployment. Key measures include threat detection and prevention, data availability and integrity, incident response, encryption and access control, and resilience testing. Prioritizing data privacy entails identifying sensitive information, limiting retention, and applying preservation techniques.

Despite much progress, ensuring fair, ethical, and unbiased AI remains a daunting challenge. Such consideration encompasses the representational diversity of training datasets, as well as design principles aimed at avoiding or detecting bias, fairness definitions, and mitigation strategies. In response, guidelines for considering AI systems' ethical implications during the design phase have been developed, focusing on five principles: safety, testing and validation, nondiscrimination, privacy, and explainability.

Modern organizations are under pressure to balance compromises in the performance of socioeconomic systems and environmental degradation. Autonomous enterprise systems equipped with self-learning and self-optimizing capabilities can support continual performance improvement based on past experience.

10.6.2. Bias, Fairness, and Auditability

An autonomous enterprise exhibits differential patterns in autonomy and decision-making across its functions and operations. These patterns create decentralized operating models that require fulfilling service commitments while adopting policies consistent with the organizational strategy. The specific risk patterns generate new service, valuation, and compliance requirements; addressing them becomes implicit in the operations rather than following standalone procedures.

Bias and fairness represent intact problems as autonomous systems deploy algorithms that take decisions on behalf of humans in various critical functions. Predictive models in any function can contain bias due to skew in the training datasets or algorithm design. Such problems will continue as long as algorithms are mainly governed and designed by humans. Empirical studies stress a comprehensive definition of fairness; fairness-aware algorithms are essential in critical functions (e.g., recruitment or loan allocation). While autonomous models can mitigate bias through self-diagnostic measures, they would require third-party auditing. Fairness-aware methods can ascertain bias in autonomous-operation algorithms, either in training or post-deployment phases.

10.7. Conclusion

The evolution toward autonomy represents a major shift in enterprise computing capabilities, with potential benefits for performance and risk management. A broad range of enabling technologies is progressively reaching sufficient maturity and scale to support truly autonomous enterprise operations. Such operations go far beyond traditional ERP systems or automation, and their realization will require careful attention to new forms of governance. By abstracting the characteristics of autonomous enterprises and self-optimizing enterprise systems, it is possible to outline a framework and define crestablished key validation criteria. From this foundation, the application of the concepts across core enterprise functions—defined broadly to encompass supply chain and operations, finance and risk, and the necessary supporting services such as IT and security—suggests that autonomy can indeed yield substantial advantage.

Reflecting on the future of enterprise systems beyond product lifecycles and development installations reveals an enduring evolution toward greater autonomy, not merely for lower-cost or pay-per-use business models but, more substantively, for greater performance. Five interrelated considerations emerge. First, pioneering work in a wider range of enterprise functions—currently Logistics, Production, and Finance—will expand the body of knowledge on autonomous enterprise systems and their application to functions that are currently less amenable to direct automation. Second, a critical reflection on governance considerations surrounding such systems will underpin future and broader applications, allowing for more radical, less incremental, explorations of gaps and innovations. Such a reflection makes it possible to monitor and discover both the natural organizational boundaries and the necessary coordination mechanisms for an autonomous enterprise ecosystem, thereby avoiding the pitfalls of fragmentation, abdication of oversight, and loss of stakeholder value.

10.7.1. Future Trends

Trends among optimising autonomous-and-self-optimising Enterprise Systems include a shift towards more autonomous decision-making, greater complexity and sophistication, self-organising structures, and smart data protection. Enabling technologies such as Autonomous Planning, Reinforcement Learning, Meta-Learning and Generative AI will be used in combination with more traditional methods to address problems appropriate to the capabilities and potential limitations of each method. Processes such as budgeting, risk management and cyber-threat prevention will have to be gradually adapted or rebuilt to become compatible with the idea of autonomous-and-self-optimising Digital Business Enterprises. The Acceptable Deviation Expressed Element (ADEE) will provide common ground between different departments and problems as exploration and exploitation routines traverse a multidimensional solution space.

Data Fabrics will also grow in complexity, especially in supporting Data-Driven Decision-Making and Adaptive Control systems. Information that is replaced much more frequently than it is consumed may have to be rethought. Newer Data Fabrics will focus on low-cost-on-average storage and high completion speed. Privacy-preserving methods will see further surveillance debates as the use of confidential data in hidden traces violates the risk-utility trade-off of those whose data are exploited. In the intense-challenge-orientated world, Data Fabrics will keep a high number of candidate solutions in more extensive parallel connections for faster service-time speed. Data Quality controls will also have to be improved as each Bias-Removing Method grows its own Bias-Creating Limitation with new Forms of Risk involved for the society as a whole. Functioning approaches can be finally acceptable as appropriate tools to mitigate the problem..

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