Deep Science Publishing, 2026
https://doi.org/10.70593/978-93-7185-592-1_10

Chapter 10: Transforming Organizations into Intelligent, Self-Driving Enterprises

10.1. Introduction

Organizations are grappling with several large-scale, profound, and interrelated transformations as a consequence of the dynamic resupply of capabilities made possible by interconnectedness in general and computing in particular. Work that people need to do is being automated: the nature, scale, timing, and location of routine work assignments are parameterized and orchestrated by resource management systems, allowing many enterprises to operate with small, flexible workforces. However, these dramatic changes bring new layers of complexity and uncertainty. Global events, such as trade wars and pandemics, create liquid supply-and-demand situational intelligence. Competitive AI- and robotic-first propositions change the rules of engagement in virtually every market. In this context, becoming more agile in scaling work and decision volumes is increasingly important. The willingness of enterprises to delegate key strategic and/or tactical decisions to AI-enabled systems rather than rely solely on human judgment is therefore hardly surprising and represents an exciting new frontier.

Such "autonomous" decision-making is actually taking place at two levels. Nutcracker decision elements, or subdecisions that can irresistibly and accurately be made by machines, are increasingly (and in many contexts successfully) allocated to AI. However, as the majority of decisions are collective, organizations also need to establish control methodologies enabling the autonomous execution of decisions located higher in the decision hierarchy by coalescing the nutcracker decisions across the relevant functional silos.

10.1.1. Background and Significance

Underlying historical drivers and corresponding industry shifts toward autonomous enterprises imply that a crucial—perhaps even defining—transformation of the organization itself is on the horizon. If, as claimed, autonomy across the enterprise is becoming a requisite to succeed in an increasingly volatile world, the challenge is integrating the multitude of steering and sensing elements—many of them themselves complex and adaptive—into a holistic, autonomous enterprise capable of automatic, adaptive, and intelligent self-driving. Addressing the resulting question—How should an organization be transformed into an intelligent, self-driving enterprise that can operate autonomously in a complex, unpredictable environment?—is important not only for business information systems, but also for the wider IS field. A response has the potential to (1) identify data-driven information technologies and associated architectural capacities required to implement such transformation, (2) clarify how these technologies enable higher levels of autonomy at the organizational level, (3) delineate the fight side for their use, and (4) determine their responsible and ethical use in complex environments.

To this end, an intelligent enterprise is defined as one that embraces a barrage of closely interrelated and mutually reinforcing innovations in artificial intelligence, machine learning, automation, and other data-driven information technologies. These organizations are said to place their data at the heart of the business and develop 'data fabrics' that encompass all its analytics-related functions, thereby ensuring timely access to trustworthy data for its human and machine decision makers.

Fig 10.1: Transforming Organizations into Intelligent, Self-Driving Enterprises

10.1.2. Research design

Enterprise transformation into self-driving organizations is of pressing relevance and challenges the traditional idea of steering and controlling enterprise creation in simple linear systems. Historical drivers originating from the pursuit of mass production and economies of scale, economies of experience, and value chain integration were aimed at building and taking control of machines performing labor—the Second Industrial Revolution. Processes within these machines became defined, perfected, and automated as an engineered, deterministic control board expediting execution while steering and controlling overall operations. The advent of artificial intelligence (AI) has enabled businesses to build new systems aimed at servicing consumer value through intelligence at both demand and supply operators. The industry 4.0 concept discusses a new epoch and revolution framed by combining cyber-physical systems, the Internet of Things (IoT), and the Internet of Services. A new self-driving enterprise, therefore, is built whereby most decisions, from consumer interactions to the production and delivery of value, are sourced, verified filtered, acted upon, executed, and closed autonomously by the enterprise as a whole—forming intelligent self-driving hybrid systems capitalizing on the automation principle.

An intelligent enterprise is operationally defined as an autonomous organization, endowed with intelligent capabilities, continuously co-creating, delivering, and capturing value in a business ecosystem. Despite widely varying definitions, the presence of generative business intelligence at the core of definitions suggests a distinguishing feature. Although industry components are semantically defined by a set of communication protocols enabling machine-to-machine control of factory robots, with wild predictions on volumes of billions of connected sensors and actuators, no industry 5.0 aspect discusses the remapping of business, service, retailing, production, support service, and value network processes to be self-steered and self-controlled by intelligent capabilities.

10.2. Conceptual Foundations of Intelligent Enterprises

Enterprises are defined as intelligent if they synthesize the four cornerstones of enterprise architecture—business, information, application, and technology—by incorporating AI, automation, advanced analytics, and data fabrics within their data architecture. Although several competing definitions exist, success in implementing intelligent enterprises cannot be achieved without all four of these architectural capabilities enabled by the four cornerstones. Traditionally separate domains such as artificial intelligence (AI), machine learning (ML), robotic process automation (RPA), cognitive automation, real-time data architecture, data governance, data stewardship, data quality, accuracy and lineage, event-driven architecture, streaming platforms, and complete end-to-end interoperability, among others, must now be interwoven into a driving data fabric.

Evidence of enterprises with these cornerstones has begun to emerge in numerous case studies. If the consolidation and integration of leading-edge technologies—including AI, ML, intelligent process automation, RPA, and a real-time data architecture enabling the complete interconnection of all aspects of other technologies and data sources across and outside the enterprise as a full data fabric for machine learning and data analytics—can be woven together into common operating environments that harness the full power of continuous-delivery software, then delivery of planned business products, services, and capabilities will become easier and faster to achieve. Implementation of edge computing and storage will remove the latency in delivery of the vertical stacks for these products and services and support their delivery for mass machines and devices.

10.2.1. Definitions and scope

Intelligent enterprise is not a synonym for a digitized enterprise or a digital enterprise. It encompasses all these ideas while being more encompassing. The idea lies in an enterprise that is not only capable of making autonomous decisions but is also constantly focusing on improvement. Which is not the same as saying that the enterprise has the capacity to be better than in the past. An enterprise that is constantly learning about its environment, constantly adapting, and can properly redirect its ambitions takes a better long-term path in comparison with one that can autonomously take decisions corroborated by the more up-to-date information.

The classification of intelligent enterprise as an enterprise that is capable of making autonomous decisions and focusing on improvement must be understood in the context and of the data that can be made available for this purpose. Both the autonomy of decision-making and the cycle of learning are two sides of the same discussion and involve the decisions of an enterprise, its governance, and the ethical pillars used to guide these decisions – governments and regulations. It is an enterprise that is able to deliver sufficient transparency to permit society and entities that have strong relationships with it to corroborate that its data, rules, and algorithms are globally acceptable.

10.2.2. Core technologies and data architecture

Core technologies such as artificial intelligence (AI), machine learning (ML), robotic process automation, intelligent process automation, and knowledge process automation provide the necessary framework for realizing the intelligent enterprise vision. Data fabric, a cohesive design philosophy with interoperability at its center, aligns and combines silos across hybrid multicloud environments. Data as a product, applied with strong data governance and stewardship principles across the enterprise, enables predictability, consistency, reliability, and context. Data governance not only addresses quality, lineage, stewardship, and life cycle maturity but also exposes data provenance and certifying attributes of completeness and trustworthiness.

A design that considers open, event-driven architecture patterns simplifies the integration of data sources and lowers the operational cost of delivering high-quality data to users—orchestrating across streaming data, data warehousing, and data lakes. An intelligent enterprise requires a data fabric that develops a real-time mirror of the business (or a near-real-time reflection for industries like banking), achieving low-latency data supply in close to real time. Businesses turn to real-time data architectures to support new business use cases, from fraud detection in banking to supply-demand matching in transportation management and customer behavior detection in e-commerce. An event-driven architecture (EDA) can respond quickly to new business conditions, allowing business rules to be written as code. Such applications resonate well, by design, in a streaming world and give organizations a major competitive advantage.

10.2.3. Governance and ethics in intelligent systems

Governance and ethical considerations guiding machine learning or automated decisions must be clearly articulated. Transparency in decision systems, even if that means striving for interpretability rather than total comprehensibility of decision criteria, is a prerequisite for user confidence. Well-defined guidelines and rules must ensure the correct balancing of risk and reward levels in AI-enabled decision-making whenever a human is not present. An easily accessible log of how each decision was taken facilitates tracing, auditing and accountability for every machine decision. The stronger the autonomy given to the systems, the more reliable these mechanisms need to be to avoid potential damage.

One aspect of trust and safety is the definition of an internal and external how rule specification with the necessary minimum level of detail and exhaustivity. Another aspect is the establishment of computer-supported mechanisms that evaluate the level of confidence in the decision taken given the current internal and external context. These metrics allow a human decision partner to agree with the decision taken, check and approve it, or require a refraction of the decision as well as the assessment of the decision taken. Transparency aids the user in understanding and using system-generated recommendations on who should act and how for an automatic execution, control or navigation of the decision not to be taken by the machine.

10.3. The Self-Driving Enterprise: Principles and Mechanisms

Autonomy at the organizational level is paramount for becoming a self-driving enterprise. This entails enabling decisions to be made autonomously by various enterprise stakeholders and automating decisions made on their behalf. Deciding how much autonomy can be extended to any role—in this case, resources within the organization—follows the same principles as any other decision: autonomy should only be given wherever it can be handled effectively. Use cases and workloads are key factors guiding this decision. Factors affecting the allocation of autonomy should be tracked across the enterprise through control planes and interpreted using context as a reference.

The self-driving enterprise has a governance structure that overlays the control plane and is responsible for autonomies exercised in contexts where the adopted principle is "delegate and forget." These decisions should be under audit, and their traceability, provenance, and sources of inequalities should be clear whenever a pattern emerges. For any decision made in an autonomous context, decision provenance, traceability, auditability, and accountability mechanisms should be in place. If the enterprise has sufficient understanding of both the process and domain, learning loops can support continuous improvement and adaptation. Otherwise, feedback should be viewed as an opportunity to correct existing model or process failures.

10.3.1. Autonomy at the organizational level

Autonomy at the organizational level can be understood in terms of different decision autonomies assigned to various organizational units. Providing the right autonomy level to each unit is critical; otherwise, all decision authority delegated to lower levels would bypass the control planes that execute enterprise and functional strategy, manage the enterprise's main capabilities and unique selling propositions, or assure enterprise-wide coherence and collaboration.

Control planes constitute the basis for strategy safety and coherence in a self-driving enterprise—they are found at the enterprise and functional levels. However, they cannot police operations and make all decisions in real time; their design minimizes the decision space of autonomous units around frequently tackled operational decisions while allowing those units to operate largely independently for many decision types, particularly in the short term. Governance overlays ensure that decisions made without higher-level approvals meet stated criteria or risk being subject to further scrutiny after the fact. They enable real-time demand-supply imbalances to be addressed without negatively impacting enterprise performance.

The decision autonomies of business units, autonomies delegated to center-of-excellence teams, and decision tracing and auditing mechanisms are the three aspects of organizational autonomy that are most critical to the intelligent enterprise and self-driving experience. Such autonomies need to be carefully designed and adjusted to optimally balance the competing objectives of quality, risk, speed, and cost in the various types of decisions being made.

Fig 10.2: Autonomy at the organizational level

10.3.2. Decision provenance and accountability

Provenance includes aspects of decision auditability and accountability, as well as requirements to build trust in algorithm-driven decisions. Auditability captures the ability to reconstruct the decision-making process in sufficient detail to verify its correctness. Governance and control mechanisms, on the other hand, delineate organizational principles and rules that ensure the system evolves toward its desired, trustworthy state. Questions of auditability are the least concerned with actual trust in the decision-making process, whereas trust is the main focus of the governance issues.

In line with the considerations on auditability, establishing decision provenance requires decision context to be added to assisted or fully algorithmic decisions. This context is not merely a justification that helps humans trust the answer given by machine-learning algorithms, but formal and machine-readable annotations that allow detailed reconstruction of how the answer was reached. Elements that should be captured include the precise workings of the algorithm, the data used for decision making (and relevant aspects such as quality, bias, and whether it is still suitable), the configuration of the support systems, and all other elements of the self-driving organization that, in interaction with the algorithm, lead to that answer.

10.3.3. Learning loops and continuous adaptation

Continuous adaptation and improvement are essential to all intelligent, self-driving enterprises. Learning loops, reinforced by the interplay of adaptation and improvement across all layers of the organization, are key to sustained adaptation.

At the action layer, digital twins allow real-, near-, or even far-time feedback from the state of the asset. In fact, these twins span not only the physical state but also operational decisions, traffic, and external events (weather, law, social screenings, etc.). These digital twins monitor the speed with which decisions can change and autonomously trigger safety detours or reallocation of resources. This means that not only do changes from the state layer drive new decisions but that external events can also trigger detours. Such detours are not subject to the same approval rules as normal operations. They have undergone approval for their state of business with respect to speed of response rather than state conditions. The detour channel is continuously monitored for feasibility and swiftness. If it has gone silent for too long a time, long-term resource reallocation will be needed.

At the knowledge layer, data-driven learning improves the adeptness of the predictive models. Reinforcement learning from the operational decisions' successes and failures helps in selecting the best-discarded forecast. The state provides the exploration/exploitation criterion for bounds of discovery. Knowledge is opportunistically shared throughout the enterprise, allowing for synaptic connections to develop in the low-redundancy areas.

At the transformation layer, business execution can be altered to be fit for flow or fit for height. Existing AI minima and AI vertica are provided operationally exposed and provide a hierarchical view of the knowledge models for supervisors at flow or height.

10.4. Data Strategy and Information Architecture

Data is the digital fabric of the intelligent enterprise. Smooth sailing instead of tumultuous navigation, rapid cargo loading and unloading instead of long queues waiting at the docks, and the speedy resumption of services after storms rather than weeks of suspension all depend on rich, real-time, and reliable data on weather, maritime traffic, events on cargo routes, and much more. Data-fundamented decision processes supported by external data sources and automated capabilities can deliver significant business benefits. Data is the fourth factor of production.

The data strategy comprises the analytics stack, the real-time data fabric, and the data strategy, while the information architecture encompasses data scarcities and qualities, the linchpin of the analytics stack, and the event-driven architecture on top of the data fabric. About 99.5 percent of internal enterprise data is rarely used in analytics, and a mere 0.2 percent of all data is likely to contribute to important decisions. Combining data sources is as challenging for enterprises as discovering oil was a century ago. Thus, when embarking on their digital journeys, enterprises must not only identify and curate data sources that contribute to visibility and prediction, but also ensure a healthy data-scape for the data-sciences ecosystem. The analytics stack determines how business decisions can be enriched by exploitation through data-sciences models. An event-driven architecture sits atop the real-time data fabric and supports the issuance of right-time actions.

10.4.1. Data governance and quality

Data governance ensures that organizations remain compliant with regulatory frameworks and enterprise policies and that the data used for various purposes is indeed fit for use, including for analytics and machine learning. Earlier research typically suggests the following aspects of data governance: the roles for data policy-making, business data stewardship, data protection, data privacy, data quality, and data lifecycle management. Hence, the enterprise should clearly define who is responsible for the following aspects across the data lifecycle, from creation to consumption:

For any given data attribute, its quality should be assessed against the six typical dimensions. In addition, data quality should be managed throughout the lifecycle of the data attribute and ultimately be independently audited. The enterprise should also create and maintain a data lineage register that describes from where, how, and by whom the data corresponding to each key attribute has been sourced and processed.

10.4.2. Analytics stack and integration

A well-defined analytics stack constitutes the foundation for extracting value from enterprise data. The primary objectives consist of employing advanced techniques to garner insights and patterns for informed decision-making, speeding up the process of generating business intelligence reports, and minimizing human effort in generating reports. To achieve these objectives, distinct data sources need to be identified and categorized into the proper source processing layer, namely visual data sources, voice data sources, unstructured data sources, and structured data. The data processing and analytics stack is visualized in Figure 10.12. The data input layer for the analytics stack comes from sources comprised of structured data repositories. Well-defined analytics dashboards report the results of simple processing pipelines carried out against the structured data repositories.

The companies' business operations generate several discrete events, usually captured in enterprise systems and stored into structured repositories. Enterprises typically perform business intelligence operations against these data repositories. However, companies often miss capturing trends and patterns in the business operations because business intelligence dashboards analyze these structured repositories only periodically. To mitigate this limitation, simple analytics pipelines are designed and automated using orchestration engines. Such simple analytical processing pipelines require minimal effort in maintaining and creating data models since the business domain experts can easily modify business rules. Real-time alerts are generated in case of any alerts triggered by these analytical pipelines.

10.4.3. Real-time data fabric and event-driven architectures

A real-time data fabric, based on event-driven architectures, connects data sources and consumers in an asynchronous and decoupled manner. It is accessed via a modern streaming platform that supports high-throughput, low-latency, event-driven use cases. This layer enables the enterprise to consume information in real time as it is created rather than relying on periodic, batch-based feeds. A logical event data model creates a shared understanding of the events being generated across the enterprise.

Enterprises are increasingly under pressure to become more responsive; to sense, analyze, and act on changes—whether in customer preferences and behavior, competitor actions, or supply chain disruptions—in real time. As they move to more real-time models of operations and decision making, a streaming architecture extends the enterprise data architecture to support continuous and real-time analytics and the automated delivery of insights to decision makers and systems. Such an architecture allows —and indeed, requires—sourcing and consuming data in a continuous manner.

Streaming data is fundamentally different in nature from traditional data. Instead of a snapshot of the world at a specific time, a streaming bit —a tweet, a stock ticker, a GPS reading— describes a small change in the state of the world. A database query may run thousands of times a day to update some number in several business units. The effect of those individual transactions may be small, but when viewed as a stream, it leads to clear real-time trends and alerts. A data fabric built on a streaming architecture supports real-time, "event" dataflows across the enterprise.

10.5. AI, Automation, and Intelligent Process Management

AI-enabled decision processes, especially for low-confidence decisions and routine choices, can operate unassisted and at scale, with confidence metrics guiding human endorsements and interventions. AI pathology examines these decisions to enhance future predictive performance. Robotic automation executes repetitive tasks, while cognitive automation—including natural language processing, machine vision, and speech recognition—handles complex activities. Despite their advantages, such techniques do not replicate human abilities, necessitating governance and controls, as errors can deviate workstreams from desired outcomes. Work orchestration designates work segments to competent agents or offshore locations. Dynamic workflow redesign adapts orchestration in real time using a capacity indicator; a detour mechanism orchestrates unplanned work in a manner analogous to reallocation.

Technological advances open new possibilities for more effective process management. While early BPM resembled pre-packaged methods and included rudimentary modelling and monitoring tools, current developments enhance process management and accelerate BPM maturity. The private equity buyout of Appian, IBM's departure from BPM, Pegasystems' fallen stock price, and ABN AMRO's BPM business exit cast doubt over the broad market. Publishing BPMN processes incorporated into the quality assurance (QA) ecosystem and BPM solutions focused on operational control remain areas of promise.

10.5.1. AI-enabled decision processes

AI technology provides organizations with the capability to enhance decision making, augment or automate routine tasks, and live up to the belief that "all corporate decisions ultimately should be made by machines." Although certain aspects of all decisions for mission-critical activities must be subject to human intervention, supervision, or review and approval — least of all those with operational risks associated with life or significant financial exposure — steps can be taken to push even high-stakes decisions further into the machines' domain. Specifically, it should be possible to develop measures of confidence in the model outputs so that the sharing of boring, dirty leftovers can be made much stronger for those in the borderline category, where the perceived risk/benefit ratio is more balanced, and where the decision-support team might be asked to take some more extreme measures nevertheless when the business impact threshold is breached.

Putting AI capabilities into production without a proper governance framework is risky, akin to letting teenagers loose in the car park with the keys. Satisfying execution and quality requirements becomes progressively harder the further the processes are taken "over the edge." Robotic process automation (RPA) creates a product that is intrinsically brittle. RPA vests full trust in its ability to simulate human behavior in corporate applications for high-volume operations like transferring data among systems. There has to be full confidence in the accuracy and reliability of every single step, which in turn means that it is best suited for very carefully defined processes isolating easy and boring tasks —those where deviations and exceptions are not just minimal but consciously eliminated. Cognitive automation is an extension of RPA that involves performing non-deterministic tasks that depend on comparisons and pattern recognitions, areas where AI fingers in the pies have demonstrated an ability to deliver significant benefits.

Fig 10.3: AI-enabled decision processes

10.5.2. Robotic process automation and cognitive automation

Robotic process automation (RPA), also known as rules-based RPA, replicates perfectly scripted interactions with computers or systems able to perform a sequence of actions according to a predefined script. These solutions can work with third-party web applications or enterprise applications that are not provided natively with an API for automation. Examples include systems that provide customer relationship management, enterprise resource planning, or other services that organizations use. This automation type also includes connectors that allow integration with systems through application programming interface (API) calls natively. RPA is running in production in a significant share of the world's financial institutions and has become a successful area of development and implementation for many digital service providers.

Significant advances in hardware and AI technologies have enabled progress in building machines that are able to perform cognitive work in the form of unstructured data processing, such as image, speech, text, and voice recognition. Automating a particular process does not imply it is monotonous or robotic; rather, it is limited to a precise function. The robotic operator does not take decisions, understand the job's purpose, or see its objective in the wider picture. An intelligent enterprise uses AI to perform a variety of shared services operations where the speed and accuracy of a machine can reduce human load, increase consistency, and avoid repetitive labor.

10.5.3. Work orchestration and dynamic workflow redesign

Operational work in a self-driving enterprise is orchestrated to leverage real-time data and analytics for task fulfilment. Forward-looking activities are supported by human workers, robots, and AI-enabled systems as appropriate, powered by real-time data processing and analytics, machine learning, automation, AI, and (when necessary) continuous governance. Quantification of probabilities, uncertainties, expected returns, and risks enables informed decisions on whether to trust automated outputs. When decision confidence falls below an acceptable threshold or when a situation is not sufficiently well understood, human workers are invariably involved. AI outputs requiring significant judgement, empathy, or creativity are retained for human consideration, even when confidence is high.

Automation addresses repetitive, predefined, and high-volume activities. For complex sub-activities, cognitive tools accelerate and enhance human speed and understanding. Robotic process automation performs highly repeated tasks; a deputy with the same skills executes successive sequences. Cognitive process automation augments repetitive work with decision support; when overloaded, humans transfer control to AI. Process redesign for automation at an adequate scale occurs frequently. A safe-to-fail mindset nurtures supporting detours. Built-in flexibility reallocates resources among parallel tasks, pilots, and dynamically redesigned processes, enabling reprocessing of exceptional cases.

10.6. Conclusion

Intelligent, autonomous enterprises are intrinsically attractive for any organization. They form a response to well-understood technological possibilities, provide remediating and value-creating answers to known crises, and are enabling vehicles for operational enhancements and business model innovations. Pursuing the transition is not a question of "whether?" but rather of "how soon?" and "over which timeline?". Demand is first and foremost driven by stakeholders wishing to support an organization steering toward such an enterprise. An appropriate strategic portfolio balances investment priorities across the demand cycle, organizational horizons, and types of stakeholders.

The detailed specification of a self-driving enterprise provides a point of reference for organizational-level reaction kinetics that various stakeholders might explore as an address to D^4E^3 drivers and/or enabling and supporting accelerators. Alternative trajectories can offer interesting research possibilities, practical exploration, and evaluation of how well-specified intelligent, autonomous goals influence organizational behavior. Future paths are intended to yield self-evident, focused, prioritized, actionable knowledge for organizations moving toward self-driving territories. They emphasize the reliability of intelligent systems for specified business domains and services and the importance of supporting change through small-assistance levels with automation liberating time for cognitive responsibilities.

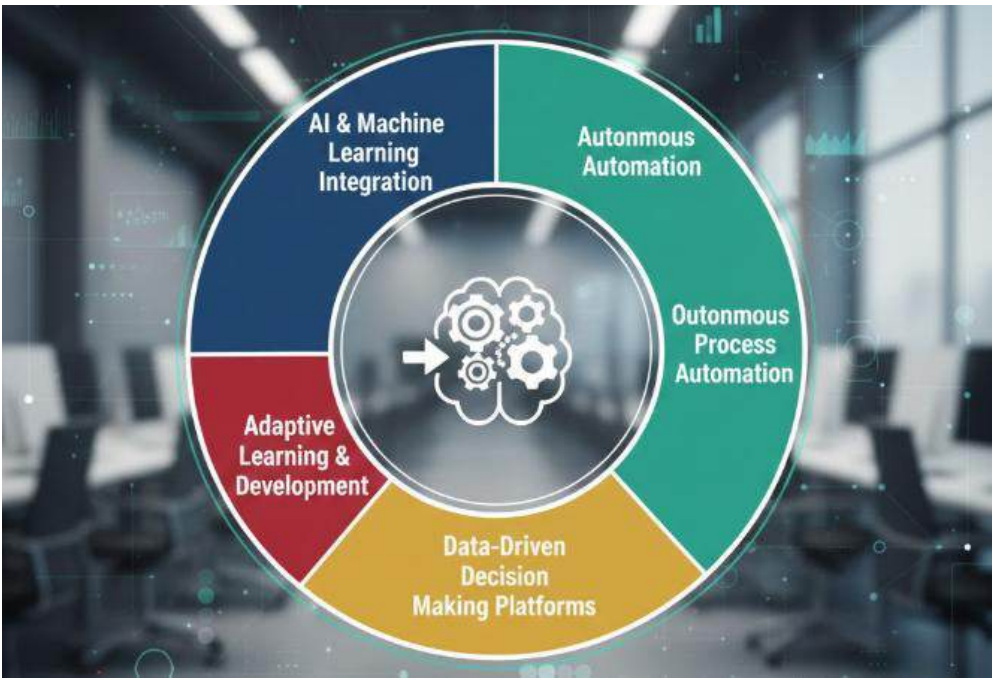

Fig 10.4: Transforming Organizations into Intelligent, Self-Driving Enterprises

10.6.1. Future Directions

The transition towards intelligent, self-driving enterprises encompasses three distinct temporal horizons. The short-term trajectory encompasses areas requiring development, codevelopment, or external innovation, with solutions amenable to ready implementation. The medium-term perspective outlines avenues for which foundational building blocks are in place yet necessitate focused co-development. Finally, the long-term scope delineates an imperative for exploration and experimentation, with current mobilization no further advanced. Many areas are ripe for immediate investigation, proof-of-concept, or demonstration projects.

Research topics form a significant subset of the short-term agenda. A systematic understanding of the capability mesh—how data, capabilities, architecture, methods, and processes combine across enterprise actors to address specific decisions, including their provenance and transparency—should support an enterprise's drive toward self-driving, intelligent behavior. Another avenue lies in the use of analytical techniques to optimize the analytics stack: when centralized, when federated, and how to connect business-action data dependencies. Such decisions are often guided by intuition, heuristics, or past practiced rather than systematic analyses. Similar techniques can map and optimize scaling of data source and processing deployment across the stack, from architectural master roadmap to near-real-time data-real-time, continuous, recurrent, and flat-analytical requirements, capacities, and associated data dependencies..

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