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# Chapter 11: Integrating cloud-native artificial intelligence in tax technology solutions

## 11.1. Introduction

Rapid advances in technology are causing finance departments to examine the kind of digital transformation they should undergo in the future. For many finance departments, efficiency may be a concern. However, for many more, failing to make such transformations proactively presents existential threats. Facing change requires a complete examination of practices, technologies, and systems in terms of cloud-native architecture and AI completion. Transformation of the data ecosystem may require considerable legacy overhaul. This means that consolidation and knowledge management processes may be particularly important. By understanding the architecture and deliverability of data solutions, the information will be readily available with the right tools. AI completion will provide early assistance around knowledge gaps and quick time to implementation on repeatable information. Together, these two components offer the opportunity to implement an AI ecosystem that is actually actionable and a foundation for future growth.

Change means different things to different people across the organization. In parts, particularly for finance departments, AI completion may take the form of a considerable number of assistive technologies, covering simple decision chain assistance all the way up to full task automation. Some of these technologies have existed for many years, and they require considerable finance transformation effort around data discipline before they can be leveraged. Other parts may be completely new, offering technologies that were unimaginable to finance departments only two years ago. Each zero and one has its own value chain within an organization. Value accumulation will be challenged, or even blocked, from being realized. In the absence of a comprehensive cloud-native architecture for all of the organization's data and information assets, many technologies will concede a 90–99% dependency on other processes, technologies, and decisions.The objective of the study is to illustrate how functional cloud-native machine learning (ML) modules can be embedded directly into tax tech applications. This has several benefits, including avoidable huge costs of implementation and the production and maintenance of black boxes. The inherent characteristics of generic natively cloud-based applications are discussed as they pertain to the functional inclusion of a data-driven optimization capability. The integration and/or hybridization of rule-based Optimization Module (OM) into cloud-native tax tech applications is illustrated and prospective algorithms analysis. The integration of ML-OM into tax tech applications is described and the functional optimization role of ML-module is broadly considered.

**Fig 11.1:** Cloud-Native Infrastructure

### 11.1.1. Background and significance

Tax technology is not new, as various tax departments have been automating compliance processes for several decades. However, it is rapidly evolving as new technologies such as Robotic Process Automation (RPA), Artificial Intelligence (AI), cloud computing, and big data are being integrated. Although well-established systems exist, many are underperforming. Existing systems are often based on 20-30 year old pre-cloud architecture design parameters that diverged widely from tax data sources and tax legislative sources. New systems are needed that are redesigned from a cloud-native point of view, natively interfacing with cloud tax data and derived task technology. Business experts can be involved to a limited extent in Business Process Modeling (BPM) as regards needs and communication, and Technically Driven Systems (TDS) can only integrate fixed processes that do not vary over time or from a macro business point of view.

## 11.2. Understanding Cloud-Native AI

Instead of hiring data scientists individually, organizations want to build and train their own AI models using self-service automation technologies on top of data engineering pipelines and cloud infrastructure they own. Executive teams have realized that AI could provide a competitive advantage by having a technology stack that could be mastered sufficiently to take it in the right direction to suit the specific case. New employees take months to get aligned with the efficiency stack. The second generation of business intelligence (BI) automation tools did not address this curse of state entropy, so these tools are not being adopted for the problems they should address. Organizations need effortless systems that enable onboarding users continuously on what technologies suit the organization well and what is the quickest way to master them with self-service automation technologies. State-of-the-art AI technologies should be used to augment complexity management.

If the enterprise architecture (EA) stack becomes inefficient or fails to deliver value for some company activities, it must be changed. Received inefficiency is a sum of inherited legacy architectures and selected off-the-shelf tools in the industry best practices. The top-down planning of a new EA stack is rarely feasible; what first must happen is a dual velocity on all technology stack layers for exploration and exploitation. High throughput systems should be achieved that could crank out prototypes of new EA stack components, evaluating their quality in the next step and integrating them if they are sufficiently better than existing ones. The models of current stacks should be introduced, and based on graph theory, inherited design failures should be detected using old-fashioned heuristics to understand what has happened and why. The approach is to explain the behavior of existing tools, processes, and designs to save time with what is plausible to try first.

### 11.2.1. Definition and Characteristics

While there is no universally accepted definition of cloud-native AI, it generally refers to implementations of AI in a cloud-native format and is supported by cloud-native tools and protocols. Like cloud-native systems in general, this category of AI emphasizes ephemeral and stateless implementations, ease of horizontal scaling, and the use of microservices and containers to minimize operations friction. In that broad sense, this could refer to on-premises AI deployments that incorporate container-based microservices and micro-batches of data into the design. This document specifically refers to deploying AI models in a native cloud format augmented by serverless methods, real-time data analytics tools, and other cloud-native-centric characteristics. Existing and traditional approaches to AI model deployment often require the knowledge of computation, storage, and memory footprints of the models being deployed, and pre-provisioning this infrastructure. This pre-provisioning introduces a trade-off between accurate predictions and incurred operational budgets, as well as providing pressure on cloud-on-operator engineering teams to meet competing customer and operational needs. Cloud-native approaches strive to relieve users of such burdens by automating the management of infrastructure consumptions with the segregation of compute and storage. Given the availability of pre-packaged AI model containers, a cloud-native AI model deployment does not require knowledge of model implementation. The abstractions provided allow AI novices to deploy models without needing the understanding of dependencies or operational requirements. Using general-purpose DL model execution engines, users just need to specify the model container to be deployed, and those engines will take care of the rest. Without pre-provisioned infrastructure, data and paper engineers can work together generating training data in cloud object storage.

### 11.2.2. Benefits of Cloud-Native AI

Organizations incorporating AI into tax technology solutions face how to build and improve AI quickly and efficiently (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2018; Kuo, 2011). This requires moving beyond data- and model-centric frameworks. AI planning helps build, test, and run AI in a cloud-native way. Ideally, AI planning requires strong support for directed execution — executing basic operations in a direction prescribed by an algorithmic plan or high-level query. However, such support is absent in several big data platforms and programming models upon which most industrial-scale AI systems are built. Data-centric systems like Spark and Flink only offer support for nondirectional execution, forcing users to move to other less-scalable environments if they want to use directed execution. This hinders micro- and macro-level AI planning across designing, building, testing, and deploying phases of AI workflows. This leads to a new programming model that provides rich support for data analysis on a big data platform while allowing users to more efficiently build, deploy, and optimize AI workflows. AI planning is first conducted in a new platform-agnostic way through a query language. Then, an implementation on top of Spark is given. A new execution engine is proposed to simultaneously exploit both directional and nondirectional execution to speed up execution. Compared with existing vision AI agents, this is the first construction of AI agents that interactively analyze behaviors for logistics tasks. This minimizes redundant investigations and streamlines the overall analysis process.

Compared with traditional AI modeling systems, the next generation of AI systems naturally crosses multiple dimensions: AI modeling and planning, building and deploying, personal and collaborative. A ubiquitous system of AI management is crucial for both AI practitioners and the general public. Built upon one platform, this serves as a unified environment across many AI construction and reasoning skills. However, it is also nontrivial to unify such a massive set of AI tasks since they are quite different from each other. Different from traditional LLM systems dominated by few architectures designed for language understanding, next-generation AI systems naturally incorporate many modalities and architectures. Dense recommendation systems and RTP systems are the two main objectives.

## 11.3. Current Trends in Tax Technology

The demands of taxpayers working in an evolving environment have a significant impact on the tax technology market (OECD, 2021; Schreiber et al., 2008). The automated data exchange between parties on a common platform in the digital economy goes beyond prevailing formats, structures, procedures, and standards, as prescribed by many tax administrations in the modern era. A thread of different priorities in the digital economy is to accelerate the digital and cloud-based delivery of goods and services by taxpayers. Countries with different stages of tax administration advancement have different needs and experience of tax technology solutions' technical sophistication and service level, which may lead to inconsistent interfaces and poor user experience.

Tax administrations' experience with automatic data exchange has revealed that the policy design, implementation, and maintenance of their tax technology solutions need years of effort to keep pace with taxpayers' changing demands for new functions and online services and the rapid evolution of relevant information technology. However, as most tax administrations are by definition public sector organizations, they are not contractual parties of their tax technology solutions and simply recipients of services. Under such arrangements, there is no explicit incentive for tax technology solution vendors to continue investing in the improvement deliveredsolutions.

**Fig 11.2:** New Technology Trends For Freshers in 2025

**11.3.1. Automation in Tax Processes**

An increasingly volatile external environment and skyrocketing costs in tax departments drive the urgency for tax process automation (TPA) tools. This need reflects the technology gap that exists within tax departments, influencing both their IT and business strategies. Initial screening needs to be undertaken to formulate an appropriate automation strategy. The TPA maturity assessment provides a common understanding of TPA solution capabilities and identifies best-fit candidate use cases. Use-case analysis evaluates the level of automation required for each selected use case and aligns RPA and AA capabilities accordingly. In a fit-gap study, overarching business goals are instantiated on a use-case-specific basis. This assignment of TPA capabilities addresses fit requirements and identifies gap requirements that require development. The selection of use cases to be automated is independent of the underlying tools.

Aiming to implement AI in the cloud, identifying candidate manual processes involves the identification and qualification of candidate use cases in a top-down approach, and an in-depth investigation of the requirements surrounding the shortlisted use cases in a bottom-up approach. An overarching automation strategy is developed that provides recommendations on how to align tactical initiatives with strategic objectives. Selection and preparation of data sources require data integration involving mapping of source data to a target data model. Additionally, the requirements of the treatment and extraction algorithm are defined, and a development plan for production preparedness is made. In developing the production-ready extraction and treatment algorithm, the treatment algorithm is realized via cloudflow software, and an extraction algorithm is developed.

Evaluation and inspection of candidate processes serve as important steps when investigating manual processes for AI-readiness. A step-by-step approach for identification, qualification, investigation, and preparation of candidate processes for AI implementation is provided, bridging the gap between understanding business needs and identifying AI-readiness business processes. With the approach of configuring an AI-ready data environment and processes, organizations can proactively pursue AI in the cloud, driving competitive advantage through automated insights.

### 11.3.2. Data Analytics in Tax Compliance

A tax examination process includes: collecting information from the taxpayer; (ii) analyzing the collected information; and assessing tax, when warranted. It is the job of a tax auditor to analyze the information by referring to the virtual file management system (VFMS) maintained by revenue authorities as well as the information collected recently, and to decide how to execute an examination plan. The tax auditor must identify where to audit, what should be examined, which evaluation tools should be used, and how many cases should be evaluated, among other factors. There are many alternatives in making these decisions. This case describes a framework that can assist tax auditors in selecting an examination model through guiding queries. This case provides a description of decision-making approaches based on both rules and data, and, in addition, suggests the application of knowledge-based AI technologies. The decision support system developed contains various databases and expert systems as well as data analysis tools. The necessary databases and expert systems are constructed based on real data, and a few case studies are used to help develop the system.

With respect to tax compliance in Kenya, when a taxpayer conducts business in Kenya, there is the liability to pay tax in Kenya. Business corporations are also liable to the payment of corporate tax. There has been notable progress in the enforcement of tax compliance by the Government of Kenya. However, tax compliance levels have not improved steadily over the last two decades. One of the major tax compliance issues facing Kenya today is the persistent low compliance level by government corporations. Noncompliance in any restrictive environment leads to costly audits, the risk of being prosecuted, or penalties, all of which substantially weaken the competitive standing of an enterprise. A tax compliance risk management model that reflects the features of tax compliance of an enterprise that is still in its infancy provides insights into tax compliance behaviour and can assist the revenue authority in effectively allocating scarce resources towards high compliance risks without unduly punishing compliant taxpayers. A two-step framework for case selection and its implementation are described.

In general, detected case risks are evaluated and classified into different complexities and disclosed in a risk-stratified manner to auditees. Auditees can then select cases as well as the overall selection strategy. This complex case-selection scenario can lead to a condition where the case-selection process can easily turn into a cabal system where a few politicized rights, entitlements, or privileges are at play with irrational selection rules. Such complex evaluation and decision processes are normally unstructured. In such a scenario, both procedural justice and distributive justice can be subjective. This results in a need for a case-selection model where the selection process is formalized and the quality of the organization's decision is improved. The selection process should not be simple enough to ensure an objective basis for fair process either because fairness becomes meaningless if the process is highly subjective.

## 11.4. Integration of AI in Tax Solutions

The rapid development of companies, especially in the technology industry, brings both purpose and threat to Tax Technology Solutions (TTS) departments.

They have to reconcile speeding up the development of tax technical solutions that meet overall company needs while ensuring compliance with tax regulations. This dilemma can be alleviated with the help of an established, configurable, and well-trained artificial intelligence (AI) architecture that takes care of coding errors before deployment, the adoption of human-in-the-loop model validation, and a feedback system for continuous improvement of AI models. The AI architecture enables coding across multiple programming languages, such as Python, Java, Golang, SQL, and R.

Natural language processing is the AI model that extracts and analyzes the requirements in the project specification and tax laws. In this model, AI is provided with a cloud-native and hybrid dataset that consists of millions of tax regulations across multiple countries and business requirements across various industries. Project specifications undergo NLP processing, clustering, and semantic similarity comparisons to identify the matching code blocks in TTS's patent code base. In matches, the code will be modified dynamically to accommodate the new business needs, and it will be converted into a unit test, which contains numerous different test cases covering edge cases for code validation. Finally, besides the TTS's coding documents that were in the training dataset, several hundred thousand similar technical documents will be constantly retrieved and embedded with pre-trained text embedding algorithms. The AI will summarize the info and suggest it on software coding, reduction of false outputs, and avoidance of coding mistakes.

Machine learning is used to identify errors in the cubicle validation process of a microservice generated by other AI architecture for backend development. In the beginning, this architecture retrieves requirements for the microservice and knowledge from the company's knowledge base and crawls for similar software. It uses the requirements as input to enhance the imported microservice and generates unit test functions for validation automatically.

### 11.4.1. AI-Powered Decision Making

AI systems based on well-defined general and tax domain knowledge, containing tax scenarios and insights that allow the systems to reason and execute various decisions will unlock a quantum leap in capabilities for Tax Technology solutions. Allowing Tax experts to ask questions such as: Which invoices are at risk of misinterpretation of the underlying payment purpose? Which financial reporting risks exist? AI-backed rules, machine learning models, and simulations will enable solutions to automatically discover misinterpretations, misstatements, or any meaningful deviations from expectations on source documents and their context.

Tax solutions need to be enriched with advanced data processing capabilities like Semantic Data Wrangling and Semantic reasoning. Transformations will be needed to read, interpret, and create knowledge graphs from source documents and other data, presenting insights against rules and expectations. IDEs for business experts, allowing them to easily observe, enter, and validate scenarios and Signed Decision Trees, are needed components. Another important class of components are model trainers for machine learning and probabilistic reasoning. Usually, they require data wrangling functionality themselves, as they need to fortify the data used for training to avoid overfitting on anomalies visible in a small data sample. The result of model training processes must be tidied and signed.

The depicted architecture allows data wrangling processes, freshly transformed data, reasoning results, scenarios, models, and Signatures as data entry points for Tax Technology solutions. The proxies make it easy to access the advanced capabilities of digitalization budgets with standardized APIs of the data wrangling Framework on the one hand and direct access to various AI systems on the other hand. It is important to ensure accountability for all decisions made by a tax technology system through a traceable decision and data evolution process.

### 11.4.2. Predictive Analytics for Tax Planning

Cloud-native AI technologies help to speed up the wave of predictive analytics in tax planning use cases by enhancing compliant use cases. Predictive analytics utilizes historical data and AI/machine learning technologies, such as regression analysis and decision tree. If the solutions are built on cloud, the use cases could easily leverage big data analytics, which is better suited to machine learning algorithms.

Regulatory forecasting models predict the likelihood of regulatory action based on historical data, AI, and existing regulations. For different jurisdictions, these models can use textual data mining techniques to extract regulation changes or updates. On the data level, AI technologies can utilize big data and predictive analytics to forecast various tax audits or disputes. Audit data mining could also identify utilization anomalies and potentially fraudulent claims.

Information about new regulations, key decision-makers, or flagged transactions can be merged into one usable dataset. By continuously and automatically cleaning, transforming, and enriching the raw dataset, business units could spot compliance breaches more efficiently. AI and cloud-enabled solutions could make and augment predictions of possible regulatory actions, through considering inputs such as business unit and regulator characteristics and historical data on compliance breaches. Business units would be provided with a list of predicted compliance breaches.

On cloud, predictive analytics for large and complex datasets can be sped up. Moreover, the deployment and refitting of decision trees are simpler and more automatic, thus reducing time and maintenance efforts. Predictive analytics usability is enhanced too; results can be easily visualized. Finally, when the original and training datasets are clean and sufficiently large, AI technologies can deliver more accurate predictions and faster refitting.

### 11.5. Case Studies of Successful Integrations

Tax technology solutions (TTS) can use a Fintech stack appropriately built in the cloud and consistent with business strategies. Executives can analyze and comprehend past and current findings, including the degree of success of tax technology solutions and Fintech stack integrations into operations as a cloud-native AI. Executives can query anecdotal evidence of operations, tax technology solutions, and Fintech stack integrations via demonstrated interactive visualizations and collected PDF documents. Analysts can write prompt queries to ask about acquired findings and integrate cloud-native AI and TTS. Process improvements can occur at TTS. Also, TTS can use recently available large language models and cloud-native AI technologies that can add value to tax technology solutions fintech stack and capital markets cloud marketplace. Executives of tax technology solutions can ask about using a cloud-native AI in TTS and the Fintech stack appropriately built in the cloud. Examples of appropriate business and technology strategies can be provided. An overview of the degree of success of the integrations can be acquired by a tax technology solutions executive. One specific area can be granularly queried, such as whether the integrations have increased internal resource productivity. Publicly available PDF documents containing examples of operations in tax technology solutions can be analyzed. Operations working with the Fintech stack and TTS can be visualized, demonstrating the technology adopted and possible workings.

Tax technology solutions can access external cloud-native AI large language models of services in the cloud marketplaces and ask for acquisitions, and appropriate TTS processes can be automated with cloud-native AI queries. Accordingly, inquiries about queries to Large Language Models and supporting AI technologies can be executed to automate parts of TTS processes as a cloud-native AI technology integrated into tax technology solutions. Aggregate data visualizations can be obtained for the Fintech stack and TTS functions. Appropriate tools can be used to track, acquire and visualize metrics and external API queries/enrichments to testify to connections to different sources of truth. And the framework can have capabilities for all previously discussed example queries and acquisitions. With progress towards the cloud-native AI query expectations proposed for integrations and detailed findings beyond the high-level overview, executive decisions such as buying initial services to pilot and showcasing prospect interest can be informed.

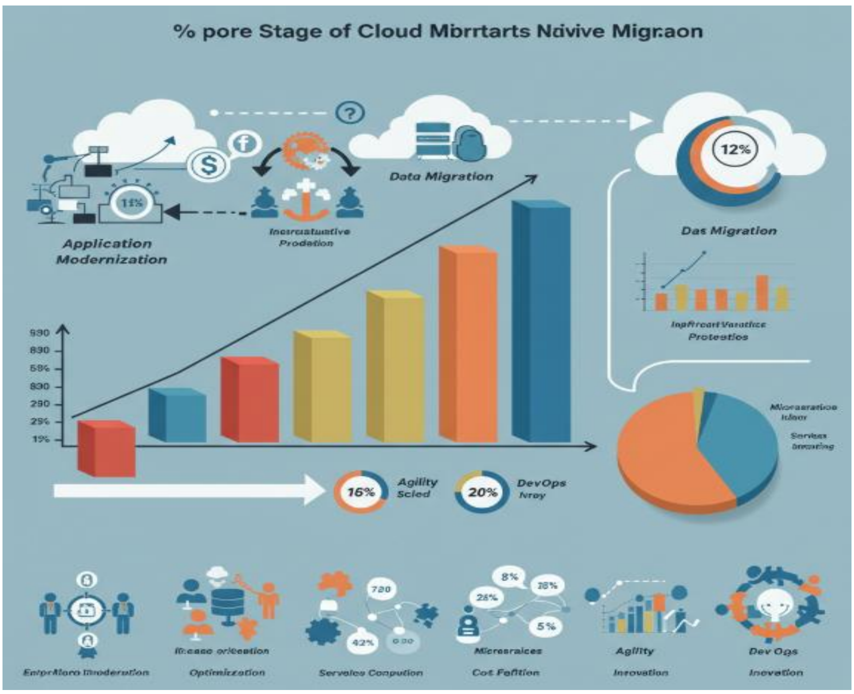


**Fig :** Strategies for Migrating to Cloud-Native under Digital Transformation

#### 11.5.1. Case Study 1: Company A

This case outlines how A reinvented its tax technology solution. A has a few major large multinational companies (MNCs) as their customers in the global market. Due to the complexity of tax regulation and drastic changes every year, tax departments rely on computers for calculation and simulation. For their enterprise solution (ES) product, A has built-in regulatory rules for the above customers, e.g. to check whether an obligation is declared on the tax return before filing. However, with the regulations of tax jurisdictions being changed every year, A frequently needs to test and rewrite the rules to guarantee the correct operation of the ES product. The traditional solution is to employ hundreds of practices and to allocate resources in large design teams, but that leads to cost inflation. A proposed several options. Under the business-as-usual option, A would hire consulting companies to maintain their legacy project and test the ES solution. The negative impact would be a loss of technical know-how and degrading quality. A considered building a machine-readable domain-specific language (DSL) in-house: using semantic web language, a tax jurisdiction coder translates the regulation into mechanics, and AI would be employed for rule generation and transformation. A also considered rewriting their product in the C language for better performance.

The discussion on option quantifications revealed a misconception by the technology director. Recent developments in AI-powered rule generation and transformation models have led to remarkable effectiveness. However, A had doubts about whether tax practices are capable of producing quality specifications comparable to university professors. Due to its high stakes, A also has reservations about putting the model on a cloud platform. While it is important for AI technology suppliers to specify and support the usage of the model, it is incumbent upon A to spew out test cases, coordinate the tuning of the available algorithms on Tier-1 cloud infrastructures, and integrate the AI-generated specs with the ES product.

#### 11.5.2. Case Study 2: Company B

The project was about artificial intelligence applied to tax technology solutions. A major tax administration company with global reach was chosen. Compared to Companies A and C, Company B had a significant presence in the development of tax technology applications but did not have as extensive a range of cloud-native applications. In the past decade, constraints of legacy tax software systems and increasing digitization demands from global tax administrations have led the company to work on transitioning the architecture of their major applications to modern cloud-native architectures.

Company B expects that in tandem with this shift to cloud-native applications, the use of modern advanced AI technologies can be integrated into their tax technology solutions to deliver more value to clients. These advanced AI technologies include natural language processing, machine learning, deep learning, and automated decision-making. As a product director was quoted, "traditional technology has its limits, and it doesn't deliver 100 percent." Hence, the application and integration of cloud-native AI technologies into their existing and new tax technology products is considered a key strategic priority.

Current tax technologies of Company B mainly consist of traditional enterprise applications, which are mostly shrink-wrapped applications supplied to clients to run in their local data center. Since artificial intelligence, particularly ML technologies, require huge quantities of data to train models and govern its usage, core data is transferred and stored at the company’s data lake first. Cloud-native data governance platform that can enable the management and organization of data collections to adhere to compliance requirements is developed. The company’s mission is to ensure that they can provide the utmost organizational level security while making sure that no client data leaves their domain during this process in accordance with data protection regulations.

## 11.6. Conclusion

This chapter explores how the fast adoption of cloud-native AI has affected tax technology solutions, examining how the changes made at a high-level architecture or platform layer alter the way tax technology is developed, configured, integrated, and operated. Tax technology providers are increasingly turning from on-premise solutions to cloud-native architectures that leverage new platform technologies, intelligent automation, and extensive in-system jurisdictions and compliance knowledge. These architectures typically involve components that operate in a cloud-native and data-centric way, or third-party-provided components that integrate using public APIs.

The resulting solutions can be implemented, maintained, and operated at lower cost than traditionally built systems, but only if the costs of implementation, maintenance, and operations have a significantly lower limit than that of traditional systems. The innovative potential of AI from a tax technology perspective and sketch out the model of a cloud-native AI tax technology solution. Tax technology solutions need to be capable of data integration, evaluation, processing, and monitoring. To accomplish this effectively, they should include data architecture, engine architecture, processing architecture, monitoring architecture, and storage architecture. Data integration can be achieved through a combination of data ingestion, data preparation, and data governance.

On the data ingestion side, ETL pipelines should be built to extract data from various sources, and take precautionary measures to avoid negative effects without considering compliance or regulation. Third-party API connections need to be taken care of to avoid breaking changes, invalid API keys, a lack of reverse updates, and data aging. Controls need to be in place to avoid delays in critical changes and self-service data onboarding. On the data preparation side, major tooling should be monumented to signal halt to expected processing errors and needs to take care of N+1 problems and performance issues to distribute processing loads evenly. This is especially challenging with heavily interconnected graph data and related refactoring processes.

On the other hand, the lack of transparency, in origin and purpose, is considerable. Therefore, it is crucial to develop understanding, awareness, and controls over potential failures. Robustness, covariance and drifting style changes, and temporal drifts channeling incorrect modeling decisions are just some examples of failures that need attention. For cheaper and faster evaluation architectures, outdated engines exert high demand on deployment and maintenance, possibly hindering competitiveness seriously. Consequently, re-evaluating the engine and possible new architectures is crucial in preparing for growth.

### 11.6.1. Future Trends

Recent developments regarding Artificial Intelligence (AI) have made it far easier to harness large quantities of data. In the past few months, the introduction of easy-to-use tools like ChatGPT has alerted a wider audience to the possibilities of Cloud-Native AI.

Many of the topics discussed earlier (like Natural Language Processing and Machine Learning) suddenly seemed more practical and actionable . There have been some valid concerns regarding these capabilities, including regard for security, intellectual property, brand reputation, and workplace culture. More traditional forms of Artificial Intelligence (the algorithms behind the scenes) have been running for years and have successfully managed many of those concerns. However, on-premise legacy systems have stifled the promise of true Artificial Intelligence usage by limiting access to some data sets. In the more traditional systems, it was easy to augment service and limit workspace entries, but in the new world of Cloud-Native AI, data and information barriers are gone. Users clearly want the power and ease of Cloud-Native AI, especially if it can be applied to the most recent data. Without proper attention, the concerns have an opportunity to balloon.

Over the next few years, true Cloud-Native AI will become more prevalent. While some might currently be too cautious, that caution will give way to aggression as tools emerge that need to be kept confidential and potentially give competition an advantage. All of these tools were built in an arms race to access the best data and speed up their models. Everything that could be worked on quickly was released for public use—mostly for free. In a world already filled with 'deep fakes,' there is plenty of room for mischief, and using these tools, it’s easy to see how they can be misused in potentially harmful and damaging ways to brands, individuals, and reputations.

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