Deep Science Publishing
https://doi.org/10.70593/978-93-49307-44-5_12

Chapter 12: Developing a strategic roadmap for artificial intelligence-driven, cloud-native enterprises in wholesale, finance, and insurance

12.1. Introduction

The rapid rate of developments in Artificial Intelligence (AI) and changes in customer expectations herald a new technological frontier. Using technologies powered by AI will fundamentally change the businesses of Financial Services and Insurance players. Much like cloud computing opened up new growth avenues to those enterprises willing to leverage it, a whole set of new opportunities to improve the efficiency and effectiveness of customer and employee interactions is emerging. However, much like other digital transformations preceding it, companies need to invest to capture the upside benefits before rivals leapfrog them or turn them into loss-generating value destroyers.

The concept of Generative AI, which is broad-reaching and includes various technologies with different levels of maturity, manifestation, and impact breadth, for example, from modeling pseudo-foundation models to dedicated fine-tuning models, age of data and training sets, is shaping executive agenda globally. Applications in Retail are improving customer engagement and efficiency exponentially. This context is unlike historic digitization waves because now the technology is about automating ‘intelligence’ rather than rote processes. Decisioning occurs at a vastly greater velocity, volume, and variance, and again much of this is invisible automation.

In Wholesale, Financial Services, and Insurance, Customer experience/user interface, AI capability maturity curves, and operating model architecture are the focus areas for executives aiming to reap the benefits of this wave. This roadmap is intended to help executives in those sectors build a clear view of their as-is situation and get aligned with the broader enterprise on a to-be vision of an AI-driven, Cloud-native Enterprise. It provides an early view of opportunity areas, interdependencies, and next steps toward building a strategic roadmap capturing the maturity, cost, effort, and reward of a pragmatic map toward AI-driven, Cloud-native Enterprise. This will be complemented with a view of the AI opportunities across each impact area, organized across their generic topics: from Foundation Models through AI-enabled Digital Worker and Intelligent Business Process Management.

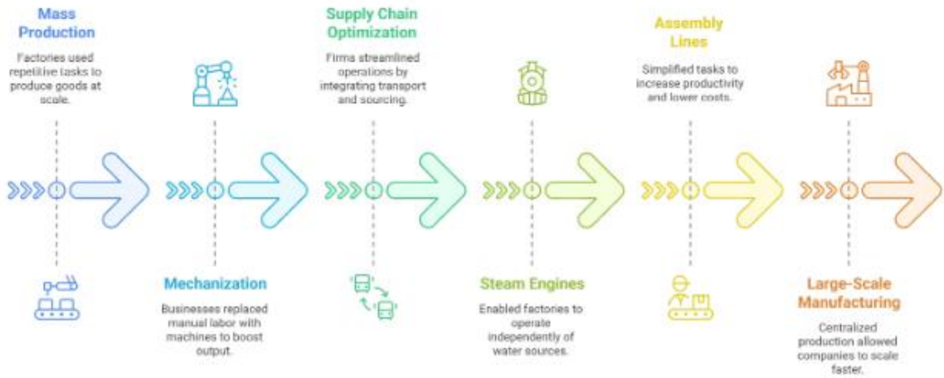

Fig 12.1: The Evolution of Business Strategy

12.1.1. Background and Significance

This presentation looks at the potential and significance of semi-structured knowledge representation as a basic building block of an AI-centric economy. It presents an overview of the necessary building blocks and their principles, including prior and new languages, ontologies and knowledge bases, and building block patterns. Traditionally, knowledge is either linguistically represented as language and documents, or semantically represented as ontologies and knowledge bases. Semantic knowledge representation means that knowledge is represented formally in machine readable manner so that machines can reason, interpret, and infer from the knowledge. While there are many advantages of knowledge representation, there are also many shortcomings of the traditional approaches to knowledge representations. In typical implementations, knowledge bases are constructed in dedicated languages, and this normally needs specialized expertise. Although knowledge bases provide a basis to support AI methods, such as logic-based approaches, these methods normally do not support scale, and this scalability issue holds for the representation languages as well. Emerging AI methods instead use information mined from documents in a less structured manner. These machine learning methods have undergone an impressive development in recent years, yet they typically cannot guarantee the quality and the safety of the delivered information. To avoid such shortcomings, it is essential to represent knowledge and information both linguistically and semantically in AI applications. Such semi-structured knowledge representation opens up a vantage view to the question, how to represent knowledge in a semi-structured manner, which would be the properties and architecture of the languages and knowledge bases, that allow a semi-structured representation. It also looks at some complimentary research topics like how to convert between the representations, how to choose in new applications, and how to align and federate semi-structured knowledge bases.

12.2. Understanding AI and Cloud-Native Technologies

Since the first commercial Deep Learning systems entered the market a decade ago, reasoning and knowledge-enabled systems are enjoying renewed interest from both industry and academia (Anderson & Jones, 2023; Nelson & Barnes, 2023; Harper & Chang, 2024). Solutions relying on Explainable AI models combining learning and theorem proving are emerging in more and more sectors, with very positive economics and social impacts. Such solutions augment human capabilities, improve customer experience, monitor the fairness of automated decisions, and satisfy exceptionally stringent regulatory requirements. These solutions tackle a vast set of problems in several areas: healthcare, finance, cyber-security, insurance, fraud detection, risk assessment, natural sciences, marketing and communications, public administration, social networks, biotechnology, and electric power delivery, among others. While these segments can be further divided into more specific verticals, they share some specific characteristics pertaining to their ensemble and are well-suited for Explanatory AI services.

They deal with a very heterogeneous, rich, complex, and distributed set of distinctive data types coming from multiple sources, such as databases, SQL queries, Knowledge Bases, data lakes, and semi-structured files, where biases and unreliable evidence may emerge. In this context, intelligent agents are supported by a Hybrid Architecture, combining Explainable Learning and Knowledge Reasoning and Management modules. Recent algorithms accounting for predictions' Justification have been integrated into this architecture allowing understanding concerning a ML model's rationale in producing its predictions. The architecture includes modules for both Inductive (ML-driven) and Deductive (Logic-based) approaches. The first type is characterized by the use of Learning models to reason about properties almost directly derived from their data. The second one widely encompasses Dedicated Non-standard Reasoners applying standard/advanced reasoning methods over usually unrolled rules to infer conclusions specializing on a specific knowledge domain.

12.2.1. Defining AI in Business Context

In entering into discussions with the business side, Data Scientists and ML engineers often face a fundamental question: What is AI? From the outside edge of the data analysis team, the answer is rather simple. Numerous scientific disciplines apply different mathematical methods in combination with programming techniques to implement algorithms that mimic human behaviour and can independently execute tasks once the methods have been formulated in training data. There is a mathematical formalisation, and various libraries, tools, and frameworks exist to apply AI techniques like ML or DL implementations directly. There are out-of-the-box solutions available with no mathematical knowledge required. They require a dedicated IT infrastructure to run, data preparation and cleaning techniques to format the data suitably, and knowledgeable people who understand data and processes behind the organisation. Conversing with business laymen, however, is more complicated. A clear understanding of the variables beyond the purely mathematical sense is often lacking. The numerous, scattered items and aspects to consider for a successful integration of AI systems and most of all, the thought process "What is business needed this for?" is either not asked or nearly impossible to answer. Every organisation and business is on its digital journey, and no single AI system can solve all problems. This is a clear call for a workshop. Many aspects influence the relevance and challenge of a data-based decision within an SI system in a business context. Roughly, these can be unrelated to the AI or ML technology (including governance, acceptance, competition, etc.), designated on a technical level (software quality/maintainability, architecture, etc.), modelling domain related (data-flow design, data domain, etc.), or focused on several subdomains of the ML process.

12.2.2. Overview of Cloud-Native Architecture

Cloud-native is gaining traction among academicians and enterprises, and investigators have proposed a host of cloud-native technologies and platforms. Cloud-native adoption brings advantages for companies, making them agile and competitive in digital transformation. Nevertheless, investment and safety risks are entailed in adopting cloud-native computing. Missing deployment reference architecture and guidance on selecting the best cloud service based on available performance metrics render enterprises uncertain in making their cloud-native architecture deployment decisions. Comprehensive literature covering cloud-native has appeared. However, few studies deliver an overview of the cloud-native architecture. This paper overviews the cloud-native architecture domain to fill in the gap.

Enterprise architects can reap benefits from cloud-native architecture by leveraging cloud-native-related technologies such as containers, microservices, and service meshes. Definitions like cloud-native applications and service providers can help practitioners disambiguate terms in the field. Architecture models shed light on enterprise architects in architecting cloud-native applications. Reference cloud-native services help practitioners make decisions on which cloud services to adopt. The survey outlines challenges and open problems faced by researchers in this field.

This review presents the state-of-the-art development of the cloud-native architecture domain by classifying it into four main aspects: definitions, architecture models, reference services, and challenges. The first aspect includes definitions, principles, state, best practices, and pitfalls of the deployment of the cloud-native architecture. The second aspect deals with architecture models and realization approaches to build a cloud-native application architecture. The third aspect discovers the frequently-used cloud-native services, framework and tools on the cloud-native architecture market, and comparative analyses of performance metrics on the commonly-used services. Lastly, this paper summarizes challenges and potential directions to outweigh open problems in this domain.

12.3. Current Trends in Wholesale, Finance, and Insurance

Wholesale Banking views the emergence of Artificial Intelligence (AI) in a positive way (Roberts & Clark, 2023; Singh & Lee, 2024). This is considered as the cusp of a new age in wholesale banking where execution through AI has become important for the banks. Accordingly, the AI ecosystem is emerging as a center of gravity in the value chain of wholesale banking. The key aspects of how machine learning is transforming wholesale banking are described hereunder. Understanding of the socio-economic impacts of emerging machine learning capabilities and new hardware has usually fallen short. Machine learning is being used to automate the tasks traditionally performed by controllers and analysts in risk and finance. Many banks have still not made the shift as there are regulatory compliance and risk control hurdles that are difficult to overcome. One mode of amelioration is addressable through a vigilance regimen of AI itself. The banking sector is in a state of flux again. The trends for the future are uncertain and volatile. Macro-economic vulnerabilities and socio-political changes are rapidly altering the environment for banking. Exhaustion of the decades-old policy regime and new technologies are also altering the competitive landscape. Beyond these major tendencies, there is also the threat from cybercrime, a continuing fallout of everything digital.

Machine learning techniques are maturing to the point of getting off-the-shelf solutions from fintechs and big techs. AI is expected to capture an increasing share of components of products and services across the financial services value chain. With their vast reach and immense customer data, tech firms are able to create a better understanding of the specific needs of customers. In this way, they offer products and services that are much more appealing. As profitability comes at a cost of customer friendliness, securing the relationship with the client is of paramount importance for banks. Other major players are expected to enter the market, especially driven by potential profitability and other attractive synergies. The bank regulators are alive to these developments and are expected to start preparing the ground for appropriate policies and rules. What more traditional banks should do is unclear but either to counter the rivals or ally with them may not stem the tide in the mid- to long-term. Where AI is already in place, regulation has at best been ex-post supervised with or without severe consequences.

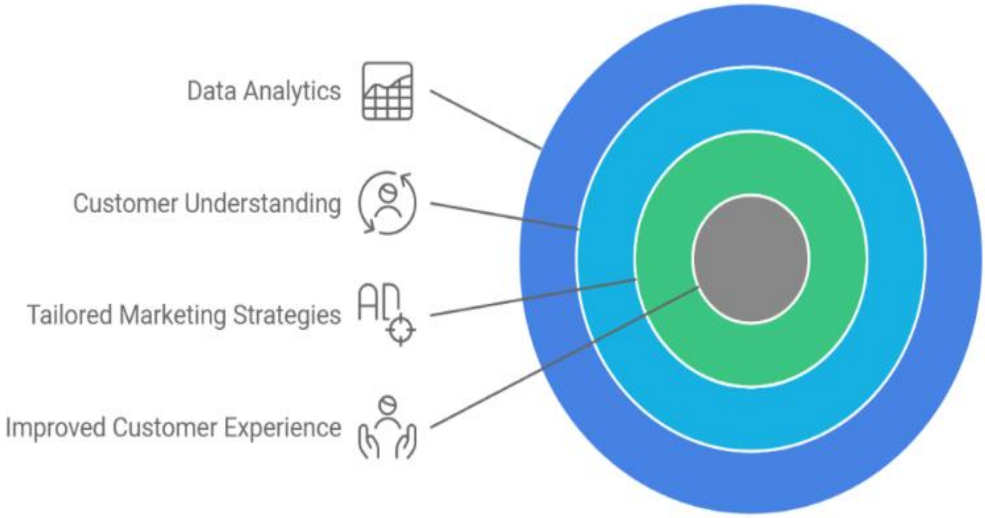

Fig 12.2: Current Trends in Wholesale, Finance, and Insurance

12.3.1. Market Analysis of Wholesale Sector

Machine learning is another form of artificial intelligence which has recently attracted attention from supply chain management scholars and even practitioners alike. Lean and responsive retailers utilise collaborative processes to push demand and supply chain synchronisation to an efficient frontier. Retailers whose demand is noise-controlled instead of trend-controlled should avoid pushing numbering of supply chains since the knife-edge difficulty would render them systematically more exposed to demand-supply mismatch. Affecting customers' perceptions and preferences by way of word-of-mouth offers first levels of gainful disruption strategies for firms. Firms most entrusted by customers were found more likely non-reactive than preferred imitators undergoing marginal but ex post success disruption. An investigation on both modelling reasons and substantial modelling obstacles has been undertaken. Analytical research is suggested in complement to agent-based simulation. The steered implementation approach has been urged for applicability and falsifiability.

The proposed modelling framework's flexibility and exploratory orientation allow handling unbalanced conditions along an integration spectrum by virtue of adaptive simulated agents interacting according to operationalised behavioural graves. Few types of research topics have been investigated including multi-dimensional blockchain integration affecting operational and financial efficiency and effectiveness of digitized supply chains; competitive advantage of prescriptive analytics through restructuring of fungible or transferable masses; tackling disruptions through digital twins that precisely and rapidly capture core processes and environmental atmosphere and convert interpretations flexibly into smart actions; performance differences between predictive and prescriptive models in handling noise and how learnt decisions can be exported from one situation to another; and modelling contentious safety standards and pricing thereof.

12.3.2. Financial Services Innovations

Artificial Intelligence (AI), a branch of FinTech, specialising in the intelligence of machines, can tackle none-financial problems in many areas, as well as the internet of things (IoT), which makes computing and analysing big data easier and cheaper. But within the finance and insurance sectors, it does face a number of issues. For example, AI changes the game; does it create wealth or destroy it? AI improves financial service efficiency; does it create a larger market or just take shares from legacy institutions? AI reduces decision-making risks; will it introduce more systematic risk in return?. This chapter only discusses financial service innovation, which naturally falls into three categories: market innovation, institution innovation, and service innovation. And in examples several AI technologies will be introduced: working on customer information like a 360-degree view and a target followed, doing effective marketing, and automating customer service; capability-creating process innovation like using pattern matching to prevent money laundering; and other internal institutional- and technology-driven ones. Market innovation aims to create more accessible financial products and services. In a broad sense, AI technologies combined with big data can integrate long-tail markets and mitigate information asymmetry. In a narrow sense, capability-creating product innovation aims to improve the efficiency of fund allocation and financial risk management issues. AI technologies including structured and unstructured data analysts using self-learning algorithms, data mining to produce undiscovered clusters, and knowledge graph technology to produce structured information and reveal inner relations can be adopted to boost loan-book asset quality.

12.4. The Role of AI in Business Transformation

Artificial Intelligence (AI) is transforming nearly every functional area of companies in every sector, and wholesale, finance, and insurance are no exceptions. AI tools can undertake data-driven decision-making at NA in knowledge work, but a systematic approach is needed to tackle the major barriers. Enterprises must create a point of view that aligns AI with their business goals. An enterprise AI roadmap must address three elements: strategy, approaches, and organizational structures. Key decisions need to be taken, and guidelines are provided. Tool-vendor lock-in, siloed workflows, and missing cross-organizational data access could impede the implementation of scalable and adaptable AI-first organizations. Enterprises embark on a journey to become AI-first that must be designed thoughtfully to address their specific needs.

12.4.1. Enhancing Operational Efficiency

To harness cloud cost optimization, enterprises must adopt a multidisciplinary approach to policy selection. Cloud education and awareness improvement need to extend to leaders and those whose throughput needs to identify opportunities for reduction. Transformational responsibilities need to be allocated to leaders having a vested interest in the transformation. Operationalizing this recommendation may vary between organizations based on political culture. Commencing education and awareness is the first step; educating leaders, followed by hands-on workshops for those with the highest expenditure, is a priority. While investment in human capital is essential, the second rule of transformational success is investment in supporting technology. Enterprises must select between purchasing pre-built products or investing in self-developed solutions. A recommendation to identify suitable tools based on common industry challenges is to host workshops at a conference center to generate discussions around the product. Select competitors currently providing industry-wide visibility as assessment quality feedback is preferred over general ballpark pricing. Engagement looking to solve specific challenges so tools can be laser-focused on delivering observable value.

Operational efficiency enhancement is often a neglected aspect within machine learning pipelines. Pre-AI operations, there are many vendors providing platforms integrating toolchains and collaboration environments for developing machine learning models, slack scheduling of resources, etc. On the other hand, post-AI operations have gained attention in more recent years with investigational journals appearing in recent years, hence tools for model hosting, monitoring, retraining, etc.. This asymmetry in attention toward AI operationalization raises questions on a few fronts, one of them being the considerable effort it takes for an individual or organization to adjust to the expectations coming with an AI model, be it by rethinking operational processes or introducing/adjusting a hosting environment.

12.4.2. Improving Customer Experience

In the financial services and insurance industries, improving customer experience and enhancing customer satisfaction has long been organizations' primary objective and clinical problem. AI technologies can facilitate the analysis of clients' personal and financial activity data to assess the likelihood and drivers of redemption and churn. Furthermore, they can also aggregate individual customer demographic and activity data across organizations' franchises as a whole to assess macro factors that can account for commotion in redemption. AI can also be used to predict the post-redemption fate of customers, i.e., whether the churned customers are likely to come back to the organization after redemption. Bespoke treatment actions can be designed to minimize their likelihood of redemption. The management objective is firstly to enhance customer experience and retention by implementing optimized strategies and dynamic actions.

To develop AI-driven models and insights, raw data must go through thorough data cleanup processes. Analyses start with aggregating data from source raw databases. Tagged transactional data tables that create real-time feed streams of data need to be summarized and persisted. One month and one year periods based on impressed activation dates are succinctly summarized. Customer attribute features, including age, asset class, and total subscription amount, need to be extracted at a point of time to present the demographic distributions of customers over time. All numeric features from raw data, such as balance, withdrawal, and subscription amounts, need to be converted to a point of time and summarized into a few lifecycle statistics. Feature grouping based on a granular point of time is also crucial when implementing clustering and deep learning methods.

Prevailing supervised learning methods implement interpretable statistical scoring models to analyze customer retention factors. Aiming for customer experience improvement, unsupervised clustering methods can be used to analyze the natural clusters of customers from behavior perspectives in order to identify business opportunities. Commonly used methods include clustering, multidimensional scaling, K-nearest neighbors, and latent factor analysis. Lifetime value analytics based on unsupervised treatment amount clustering can also be implemented to slice business strategies respectively based on customer activity.

12.5. Cloud-Native Strategies for Enterprises

Cloud computing has been employed by significant numbers of enterprises for years due to its vast advantages. Yet, a much smaller fraction of businesses have begun moving cloud-native, that is, developing applications specifically made for the cloud. This is partly due to a lack of awareness and understanding of the cloud-native architecture, leading to the exploration of on-premises or vendor-specific cloud solutions that prevent this innovative architectural paradigm from being developed further. A homogeneous platform for cloud-native high-performing applications is not available, nor is a common cloud-native application model. As a result, many organizations continuously re-engineer and reinvent established cloud-native patterns and principles. To assist enterprise and solution architects to develop a uniform concept and understanding of cloud-native applications, this paper presents a conceptual design and architecture for cloud-native applications positioned on commonly standardized IaaS services. The cloud-native application architecture comprises a reference model and a corresponding application architecture—a set of standardized application components matching the reference model services.

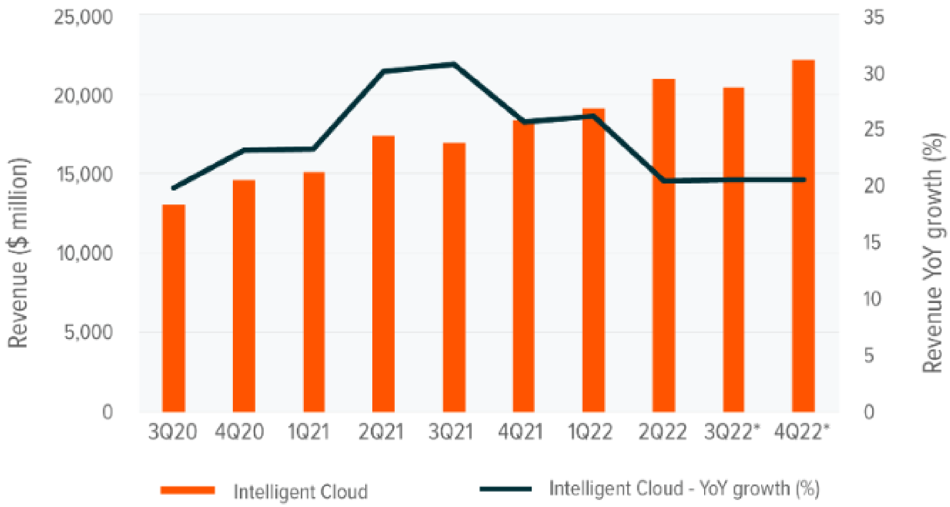

Fig : Rise of Artificial Intelligence & Big Data

12.5.1. Benefits of Cloud-Native Solutions

Cloud-native applications have quickly evolved to exploit the service-oriented aspect of cloud computing. They are multi-tenant applications which are purely web-based and can operate on various types of devices running different operating systems or using different browsers; but all that they require is an internet connection. They include application meta-repositories such as Google Apps Gallery, Office365 Marketplace, AppExchange, Apple App Store, and social networking applications like LinkedIn, Facebook, and Twitter. Adoption of these applications provides primarily financial benefits to businesses in the wholesale, retail, finance or insurance and public sector. While this promising trend will continue to grow, a number of issues will need to be fully addressed. Cloud-native applications are vulnerable to vendor lock-in conditions which lead to catastrophic situations for businesses. Numerous account closures of such applications have occurred for reasons of unexpected service discontinuation, company buyouts/closures, or new policies. Some users accuse the service providers of fraud and attempt to sue them. Still others state that they would gladly pay a monthly fee of a couple of dollars for such applications if they were available. Most cloud-sourced services are vendor lock-in prone and this aspect should be properly addressed. Some cloud service categories of PaaS, IaaS, CoLo- IaaS, Storage-E, Storage-C, or Storage-NP seem to foster vendor lock-in situations which might be especially problematic. An offering of the vendor's own service or a service of the vendor's partner ecosystem might lock-in the enterprise. An IaaS resource may be particularly difficult to switch, if a specific application is heavily adapted using a non-standard service or resource. Similarly for non-standard IaaS networks, compute resources with GP/FPGA capabilities, or a proprietary OEM computing resource.

The characteristics and types of cloud-native applications dominating the market today were discovered. Based on such a table, a taxonomy together with a Venn diagram of the class's mutual intersections was devised. The taxonomy was presented within the context of a grand scheme of the web-centric software long-term product space . The major pathways of creating a cloud-native application were elaborated on, from pure HTML+HTML5 to pure GAE based model. Both of their important instantiations using contemporary high-level technologies were sketched. The evolutionary pathways would lead to a hybrid cloud-native application commonly based on an HTML5 own JavaScript client.

12.5.2. Challenges in Adoption

AI fast tracked developments in all operations of the firm. Enterprises need deeper intelligence and robustness to unify these newly collected streams of information and unlock hidden insights. Foundation Models (FMs) empower wholesale distributed networks to integrate AI coverage in a novel manner, manage the adoption challenges, and enhance service resiliency. FMs can complement existing services to handle rare events, misinformation, and unseen operational conditions while supporting enhanced prediction. Lastly and most importantly the language capabilities of FMs can upgrade and democratize the ability of enterprises in working with quantitative data.

The adoption of FMs in a substantial way calls for resilient adaptation of both the technology and the way the firm operates. Hence enterprises need to grow in two dimensions: foundational technology and enterprise new constructs designed to build effective new operations in tandem with the powerful offered technology. In that FMs are new and evolving technology, and at the macro-operational rethinking it is a stark departure, rapid changes will happen throughout the journey and hence constant adjustments will be mandatory to counteract obstacles and unlocking opportunities.

One of the major risks to consider during rollout of the principles is the emergence of inaccurate or misleading information at the input data. Ensuring sound performance also with extremely rare radiative atmospheric conditions and at unseen distributions is crucial for relying on AI driven automation. This concern is common to all AI input systems, and the limitations of AI automation in this sense should be understood and considered when implementing services. Misbehavior of the service has a substantial operational risk. In addition to adoption challenges related to unavailability of detectors and underlying models, AI based solutions are vulnerable to adversarial attacks. Malicious alterations of the data or the systems can lead to substantial shortcomings and dangerous situations. The inter dependency among the forecasts and in a multi-agent distribution necessitates inclusion of FMs in the new operational structures.

12.6. Conclusion

In developed and developing countries alike, AI is set to unlock value that can help enterprises to recover and grow. In the longer term, AI is poised to change the competitive landscape for virtually every business and government. However, enterprises face choices that will determine whether they reap the rewards of these capabilities, or get left behind. Cloud providers will compete intensely based on AI capabilities, while hyperscalers will vie to vertically integrate value chains with AI and cloud at their core. A number of choices will be required to prepare organizations for success. To realize the promise of AI, organizations will have to select new AI cloud-ready architectures that can extend ML operations beyond one-off experimentation into the mission-critical domain. Retraining employees for the cloud generation is critical for capabilities that support the enterprise-wide adoption of AI, securing a competitive advantage. A strategic roadmap is essential to define how AI can drive innovation and efficiency in corporate processes, products and services. AI will be the cornerstone of cloud-native transformation.

Artificial intelligence (AI) is transforming business and changing the way organizations operate. Financial services firms employ various artificial intelligence (AI) technologies so that data-driven insights can help optimize business processes, making them more efficient, agile, and innovative. A strategic roadmap is essential to help financial services organizations define how AI can be harnessed to drive innovation and efficiency. AI initiatives with the greatest potential impact on corporate processes, products, and services need to be identified. AI applications need to be ready for implementation, with the management control structure defined. AI technologies are sufficiently mature to drive high-performance applications, which can improve decision-making, increase operating efficiency, create a better customer experience, and develop new products in financial services businesses. By harnessing cloud computing technologies in various aspects of financial services, AI-enabled applications are supported.

12.6.1. Future Trends

According to a forecast , the cloud computing industry will be worth US$ 210 billion by 2020. It encompasses a variety of platforms that function collaboratively to meet user requests while assisting parties in prioritizing cloud usage. Attention has recently been given to Artificial Intelligence (AI) techniques for cloud computing. The integration of Cloud Computing (CC) technologies with the other two cloud-enabling technologies of IoT and Blockchain (BC) is reviewed. This study aims to provide a categorized review of research papers focusing on these aspects. Moreover, a conceptual model representing various components of IoT, BC, and AI is illustrated. Over the past decade, the advent of cloud computing as an on-demand service through the Internet has been a major turning point in the physical world. The desired effect of computing in any company can be achieved in four possible business environments by using either cloud technology or traditional infrastructure. The cloud provides infrastructure, programming platforms, and software as an online service, thereby eliminating the need for in-house management of machines and software installations.

For remote location businesses or start-ups, cloud computing helps accelerate growth with affordable, secure, and reliable applications. It enables tailored solutions to applications with web-based distribution, yielding numerous payroll benefits for clients and resources by genuine expertise. Furthermore, dynamic scaling of cloud resources is offered with the ability to automatically add or remove resources. This cloud elasticity is accessible to users directly or indirectly, depending on the type of cloud computing model adopted. Self-adaptive resources for cloud services are categorically modeled, focusing on service demand, system architecture, cloud and client locations, types of service portfolios, and cloud providers.

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