

A Multidisciplinary Framework for AI and Data-Driven Transformation in Taxation, Insurance, Mortgage Financing, and Financial Advisory: Integrating Cloud Computing, Deep Learning, and Agentic AI for Community-Centric Economic Development

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ABSTRACT

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Taxation, insurance, mortgage financing, and financial advisory are examples of fields facing an increased demand for data-driven transformations. These transformations comprise digitisation, automation, and analytics. Artificial Intelligence (AI) has various applications in all these fields. It is presented as a structured problem for mapping both the fields and corresponding AI techniques together. Of the many techniques popular in AI research, a handful are systematically mapped against a proposed framework. The framework naturally leads to a heat-map view of technique popularity, showing relative dominance in each of the four different fields.

AI was once thought to have little relevance to practice, but has in fact been mainstream for some years. Tax debts have been audited with experimental models, savings have been extracted with various optimisation techniques, emotion detection has been used for financial risk, and AI is widely used against fraud in practice. More recently already well-established AI fields have shown promise in their first forays into the domain. For example, active learning methods have shown good early results in bankruptcy prediction. These efficacy studies also promise great reward for companies who successfully adopt the technologies. Privacy-preserving data mining confidentiality preserving approach has cut the necessary feature pool to a third of the normal pool with only a 15% cost on the true positive rate. The lower cost is especially significant as the false positive rate is up to five times lower.

Keywords: AI in Financial Services, Agentic Artificial Intelligence, Cloud Computing in Finance, Deep Learning Applications, Data-Driven Economic Development, Taxation and AI, Insurance Technology (InsurTech), Mortgage Financing Innovation, Financial Advisory Automation, Community-Centric AI Frameworks.

1. Introduction

Artificial Intelligence (AI) and data-driven technologies have been transformative in quite a number of domains ranging from tax collection, fraud detection, risk and wealth assessment, predictive maintenance, process automation, to regulatory compliance. In taxation, AI has been utilized by tax authorities for fraud detection, robotic process automation, AI-driven policy development and bespoke tax guidance. Here, it mainly focuses on four particular facilities in the field of tax and finance: tax collection for both large enterprises through transfer pricing rule matching and medium businesses through automatic VAT monitoring and reporting; insurance and mortgage

financing for private individuals and medium enterprises; financial advisory services for natural and legal persons, including savings and investment planning and monitoring, and pension funds funding compliance monitoring.

Broad range of propriety risk and benefit assessment as well as resource planning algorithms have been developed and adopted for policy surveillance, customs risk assessment and taxpayer vulnerability scoring by governments or by private companies like in case handling or in charity sector, although it is recognized that adversarial entities are increasingly developing counter measures similarly using AI and advanced data-driven methods. Otherwise, largely non-public AI and data-driven monitoring and assessment tools are more commonly used in the financial or social industry in the context of mortgage financing, financial advisory or marketing for certain products, services and risk hedging. Considering the wide access to AI and data-driven tools, and rapidly evolving and combined threats and opportunities it is essential to define and adopt efficient, effective, safe, transparent and fair rules for both massive daily-exchanged automated decision and support systems and those used by officials assessing the compliance or looking to improve the respective processes. In this respect, it is aimed in this submission to present a draft of a requirement on the future system incorporating AI and data-driven methods, with the illustrative examples from four particular facilities in the field of tax and finance, and to assess relevant ongoing actions from the system providers, policy makers and other stakeholders. It is encouraged to discuss how the presented wish list could be operationalised, what would be the success indicators and how the adequate checks and balances could be ensured.

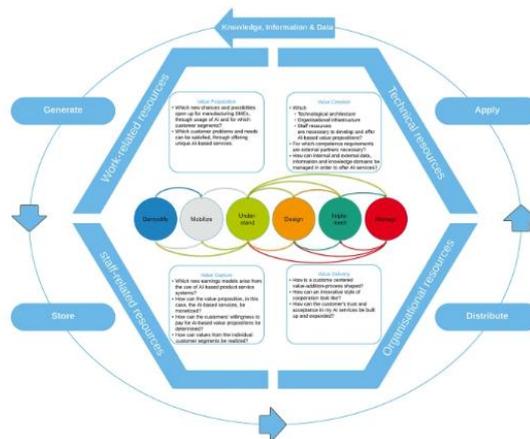


Fig 1: Design Framework for the Implementation of AI-based (Service) Business Models for Small and Medium-sized Manufacturing Enterprises

1.1. Background and Significance

The transformative potential of problem-driven strategies and problem domain-centered research in the development, deployment, commercialization, and diffusion of Artificial Intelligence (AI) and data-driven systems has received increasing attention within computer, engineering, and social sciences, as well as the humanities. The applicability of these paradigms to the domain of taxation, insurance, mortgage financing, and financial advisory, however, remains underexplored. To fill this gap, a multilevel, multilayer, and a multifaceted framework is introduced that aims to clarify the myriad of opportunities that exist along the aforementioned system lifecycle when these sectors are viewed through both a disciplinary and an interdisciplinary lens. The approach aspires to provide a comprehensive and strategic overview of how the gaps between these sectors and the latest advancements in areas such as computational, algorithmic, and sensorial possibilities can be bridged through a synergistic collaboration of researchers in lightweight and sponsored environments.

It is argued that this framework not only identifies the research, development, and deployment strategies required to address the core challenges that prevail in a modern but largely analogue taxation, insurance, mortgage financing, and financial advisory system in Europe but also adopts a governance approach to investigate foundational ethical and societal concerns emerging from the development, deployment, commercialization, and diffusion of AI and data-driven systems in these digitization-resistant sectors. Furthermore, it is suggested how the Governance Systems with Automated Intelligence framework affords the way to ensure that these foundational ethical and societal concerns

can be anticipated and addressed before AI solutions in the two problem domains become firmly embedded. Finally, by providing an actionable forward- and backward-looking research agenda, an aspiration is that, above all, this text furnishes an essential roadmap for the challenges and opportunities of developing and embedding AI technologies, model governance, and societal understanding more equitably across taxation, insurance, mortgage financing, and financial advisory sectors.

Equ 1: Data Aggregation Function

$$D_t = \sum_{i=1}^n w_i \cdot d_{i,t} + \epsilon_t$$

- D_t : Aggregated financial data at time t
- $d_{i,t}$: Individual data source i at time t
- w_i : Weighting factor (e.g., source reliability or data quality)
- ϵ_t : Noise or uncertainty from cloud-based data ingestion

2. Theoretical Foundations

Artificial intelligence (AI) is a cornerstone of the data-driven transformation of the financial industry, particularly in the divisive sectors of taxation, insurance, mortgage financing, and financial advisory. AI-driven automation and big data analysis have had a widely recognized impact on the bonding and business sentiment of loan seekers, the credit/grant assessment of loan/debt portfolios, and the trading and risk management strategies of bank and non-bank institutions. The awareness of these issues triggers agnostic financial services, which in turn may contagiously reproduce their market power over soft competition. To react, the EU has deployed the General Data Protection Regulation, a policy response to the ubiquity and implications of big data, machine learning, and marketing automation. At the same time, the perspective can be reversed, with an agent trying to persuade an AI into completing tasks that are not desirable. Such adversarial examples have been successful in areas as diverse as spam detection, planned malware detectors, algorithms, or faking face-recognition camouflage. The last orthodox reason being that analytics is a toolkit not a golden bullet. The established analytics can only get as good as the available data, and, in many respects, inaccessibility is the primary issue in the field of financial services.

Beginning with a collaborative and federated system built from mixed human and data analysis, it is shown how an analytical instrument valid in one domain may be misguided in another. The Operations Research and machine learning models, based on temporal databases and social network data, centralize, and exchange personal customer information with the resulting deleterious groupthink biases. The main issue is the paucity of most behavioral and psychological primitives, market signals, and decision-making algorithms. This need not be a necessarily daunting task. Feedback from classifiers is obtained using cross-domain adversarial learning techniques to identify superficial biases and guide the draw of more informed insights, either for policy or conception. However, it is discovered that card credit holders in economic stress exhibit conspicuous spendings increases long before the declared conflict, while this does not automatically translate into credit scoring or funds management strategies. Owing to cognitive dissonance, they might contrast real-life and predicted financial and consumption behavior, thus concealing the concentrations of predictability.

2.1. Understanding AI and Data-Driven Transformation Comprehensive legislation and national strategies have been prepared to respond to data-driven public sector developments and changes, including artificial intelligence transformation. The studies and suggested frameworks are sector-neutral, so they can be applied to the entire public sector. Nonetheless, as a demonstration, this study presents a multidisciplinary framework for the tax administrations and the financial sector, including the insurance, mortgage financing, and financial advisory sectors.

This proposed model for AI and data-specific transformation is demonstrated through tax administrations and financial industry cases in taxation, insurance, mortgage financing, and financial advisory, which are the most data-centric and AI-applicable areas in the public sector, as well. At the heart of the framework is a holistic technology and organization transformation model for AI and data-driven public sector in both policy and operations. The proposed model consists of three following levels: An overall strategic policy level framework; a comprehensive operating model with ten well-defined building blocks to create an implementation roadmap at the governmental unit or

organization level, and; digital transformation moves with detailed actions and checklists. The framework is based on the original Artificial Intelligence Transformation and the Big Data Value Creation and Reallocation models. In addition, according to the literature review and synthesis of sector-specific legislation, plans, and analyses, the main actions, constituents, and recommendations are provided to support AI transformation in taxation, insurance, mortgage financing, and financial advisory. More broadly, the combination method, portfolio widely ranging over the available technologies and algorithms in AI and data analytics, the multidisciplinary SL-DM-FI targeted research and business environment, strategies to proceed with maximum effectiveness and minimal obstacles, and appropriate societal concerns are the subjects rarely tackled together.

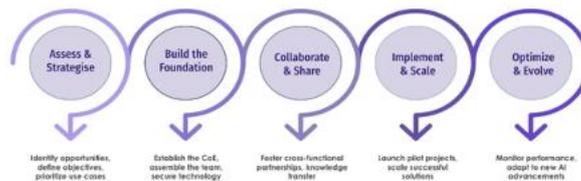


Fig 2: AI and data analytics-driven finance transformation

2.2. Multidisciplinary Approaches in Financial Services Artificial intelligence (AI) and data analytics have grown up to create substantial research, business and social impacts, and have the potential for further growth in new fields and broader domains. There are five notable directions that could play a role in the financial domain. They comprise continuing development of the existing technologies; diffusion into the areas where the relevant applications have not been deployed substantially; multifaceted research in terms of systems structure, algorithms and cases; reconsideration of the impact on the research methods and ethics in society; and development of mutually coordinated academic, business and policy efforts to deepen the impacts.

5.2.4. Reconfigurable algorithms and combination methods In the financial domain for the sector of insurance, a substantial scope of applications of both AI and data analytics technologies has been reported, even from a relatively early stage, in taxation, mortgage financing and financial advisory. These findings are interesting because the number of academic user cases is not as vast as in the areas of algorithm trading, bankruptcy prediction or credit areas based on surveys made by and the literature review.

3. Cloud Computing in Financial Services

The financial industry is generally believed to be composed of banks, insurance companies, securities companies, and other companies. However, this categorization is too broad and from a functional perspective. This paper classifies and explains them from a tax law perspective. The structure of this paper is as follows. This first section is an introduction touching upon the regulations regarding financial holding companies. The second and third sections contain detailed reviews of financial services companies in the Catalogue, respectively. The last section presents recommendations for financial service companies and the tax authority.

Along with technological advances, financial institutions, insurance companies, securities companies, and the like have expanded their functions across borders. Recently, IT companies have also entered the financial industry. These changes in the financial industry have spurred the enactment of various financial laws and systems across countries. In particular, Article 5 of the Financial Holding Company Act addresses the subject companies and other financial service companies not publicly mentioned in the holding company's registration materials. Consequently, this study examines how to categorize such financial companies from a tax law perspective and carry out tax audits.



Fig 3: AI and Cloud Computing on the Future of Finance

3.1. Infrastructure as a Service (IaaS)

Infrastructure as a Service (IaaS) is a modality dealing with cloud-based monitoring and control over the infrastructure. Taking place in a city, it typically involves utilities such as lighting, heating, electricity, garbage and water management, and organizes transport, police, fire brigades, and healthcare.

Infrastructure as a Service (IaaS) involves monitoring of the environment and of the service delivery elements. The acquired data may be used to control the actuators, where actuation brings about an observable ‘propagated’ change in the monitored data (different from the immediate change enforced by the actuator). To represent such views, the data needs to be pedestal; first, one should detail matters about the data and respective frame organization. This is slipped under CTM 19 (Common Terminology Model). et some of the service delivery media (i.e., ‘infrastructure domains’) that can interact with the environment include: PWR (Power), COM (Communication), GAS (Gaseous), WTR (Water), LIT (Lighting), VEH (Vehicular), TRN (Transport), WST (Waste), GLD (Guiding), MAU (Manufacturing), BLD (Building), and PEV (Pedestrian).

Vertical and horizontal industry-wise and function-wise decompositions of various technological paradigms employed for infrastructure control are also provided. While the vertical division is made with respect to the style of acting on infrastructure—visual, community, building, and vehicular—the horizontal one deals with ICT solutions applying to a different layer of control stacking.

3.2. Software as a Service (SaaS)

There is a market need for more practical and theoretical analysis of how Artificial Intelligence (AI) and data-driven computing (DDC) can contribute to powerful, global, and efficient paradigms, processes and tools, which are testable and addressable to the knowledge of academic, professional and political user communities in Taxation, Insurance, Mortgage Financing, and Financial Advisory. All these societally important fields are socio-technical constructs where market and bureaucratic forces operate in a delicate interplay. They also lend themselves to a formal analysis as service innovations under incomplete but evolving information. Finally, they are classic domains with a massive contribution to the GDP by many countries, thus with a high technology and policy impact.

The use of SaaS in professional computation and the analysis of its implications have remained underexposed. This paper aims to stimulate a wider discussion on what conditions SaaS may indeed offer the optimal societal value. A custom-developed framework enables a more encompassing analysis of SaaS effects. Prominent European cases are considered, including in Finland, a taxation project. The framework and the analysis also serve economists and IT-specialists by expressing and quantifying N- years dynamic net macroeconomic and technological effects (i.e. new jobs, GDP growth, etc.) of a SaaS project. The fact that effects of SaaS once agreed upon are simpler to monitor than those of on-premises software likely induces more public trials by contracting authorities. Public tenders are particularly scrutinized. The potential of SaaS is demonstrated in the public sector where the CA’s willingness to replace on-premises software is highest. When considering each type of effort on its own, the results indicate that physical interactions explain additional variance in the evaluation of mockup kits (23% of the variance).

Equ 2: Deep Learning Prediction Function

$$\hat{Y}_t = f_{\theta}(X_t)$$

- \hat{Y}_t : Predicted financial outcome (e.g., tax revenue)
- f_{θ} : Neural network with parameters θ
- X_t : Input features (e.g., economic indicators, user data)

4. Deep Learning Applications

Financial technology has ushered in a new era of transformation in the financial sector, and the traditional financial institutions are facing transformation and upgrade pressure. The convergence of deep learning, big data, and powerful computing resources is boosting the rapid evolution of Artificial Intelligence (AI) and offering enterprises deep market insight. Offering unprecedented predictive and prescriptive model capabilities, AI significantly changed products and daily operations. Banks face severe challenges because of massive data loss, financial market transformations, decreasing economic growth, and tough marketing demographics. Start-ups and Internet-based financial services were explicitly supported by the State Council and launched grand strategies. Banks habitually respond to external competitive pressures by providing multiple intelligent goods and services to foster intelligence transformation. The government further points out in the "Guidelines of the State Council on Promoting the Deep Integration of Artificial Intelligence and Real Economy". The financial sector is integrated with AI-based, data-driven, industrial internet and smart manufacturing with intelligent transformation in traditional sectors. Additionally, the firm is encouraged by the local government to use AI in enterprise management. AI models are employed in field services daily.

DL studies have lately made significant achievements in the field of social digitalization, e.g., using credit card data to recognize user habits or assessing loan default risks. The main method of DL technology is to analyze data based on data representation learning. It is a type of machine learning method. The AI behind it has been a focus of scientific and technological development and of cooperation with non-genomic engineering. There is widespread belief that AI will transform or revolutionize entire work, something like the industrial revolution and the invention of steam engines or the second industrial revolution and the approaching use of electronic devices. A common understanding of AI is that machines can perform tasks at or above human skill levels. As a commercial bank, the Industrial Bank maintained significant market share in structural and exchange rate reform after the financial sector opened up. Trusted by the national reforms and innovation strategies, the transformation and upgrade of the financial sector is a distinct feature. After the financial crisis, AI was extensively used by the Industrial Bank. Agencies, robots, and other types of trading components have been used greatly. Consequently, stock investiture has a wide selection of products and services. Many businesses transfer big data and operational data to the core enterprise department platform of the Industrial Bank, and financial markets, economic conditions, and exchange rates must be continuously analyzed. Recently, more and more are moving to deep learning (DL). Deep learning (DL) is one of the machine learning techniques of AI and is based on the neural network of the data itself. It can achieve good results for in-depth learning strategies.

4.1. Predictive Analytics in Taxation

In recent years, the availability of various types of data and high computational power has been driving various industries' transformation in insurance, mortgage financing, and financial advisory services. Combined with Machine Learning methods, such as Deep Neural Networks, Reinforcement Learning, or Kernel Methods, Process-based Data Flow, Smart Services, Explainable AI, and, in general, systems that combine the availability of data and AI.

In the context of taxation, the risk aversion behavior of firms in the context of tax evasion is studied as a Sequential Decision Making problem using Deep Q-Learning. A hybrid model of the standard R-G model with the option pricing theory is employed. In this model, profits are influenced by the firm's total earnings and enhanced by the smoothness of the tax-evaded payments. A firm plays with the aforementioned smooth earnings aiming to optimize its total profit.

A novel framework is proposed for utilizing these modern tools structured in a Process-based, Data Provision, and Smart Services fashion for the respective industries. A Systems Flowchart is introduced indicating the pipeline of

data and the analytics used for each industry. The Smart Services sub-modules are built on the premium of a leading insurance company, the mortgage portfolio of a bank, and the financial advisory services of a start-up company. The importance of Explainable AI is discussed with potential systems implementations. The advantages and potential of adding Process-based Data Flows are highlighted, raising the importance of utilizing a framework that combines the four paradigms presented.

The use of modern Machine Learning tools in the tax evasion context and the innovative framework that is proposed as a way for further industrial transformation is detailed. The Process-based Data Flow, Explainable AI, and Smart Services/Feature Engineering are also presented as a structured framework for potential researchers and industries that want to start into that realm. It is shown how Smart Services could be developed for the tax authorities leading to a more effective implementation of the system for businesses. With the help of AI, the proposed conceptual framework provides policy makers with tools for simulating the impact of different policy instruments on markets influenced by AI algorithms, for better understanding the behavior of AI-trading agents representing economic subjects, and opens up possibilities to understand the positive indirect macroeconomic implications of disproportionate regulations in financial markets that effectively prevent the full benefits brought by AI systems.

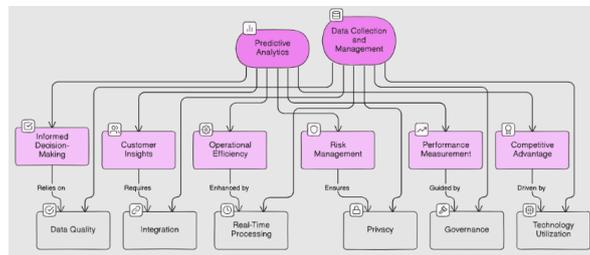


Fig 4: Predictive Analytics in Taxation

5. Agentic AI in Economic Development

Economic development refers to sustained, concerted actions by policy makers and communities that promote the standard of living and economic health of a specific area. The most recent AI strategy brings a significant positive change in economic aspects. One of those significant roles is agentic AI (Artificial Intelligence). Agentic AI is a technology that can mimic intelligent human behaviour through complex algorithms and big data for decision-making in trade, financial, and economic management activities, plus on-times adjustment of performance strategies.

Economic development, especially in the public sector, can benefit from the adaptiveness, fairness, and multi-objectivity of MARL (Multi-Agent Reinforcement Learning) much more so than other industries like robotics and video games do. However, the adaptiveness of MARL to the non-MARL agents outside the simulator is unreliable due to the diverse design and sensitive nature of the model. As concerns fairness and multi-objectivity, most public AI research is focused on MAL (Multi-Agent Learning) rather than on MARL, which avoids the in-depth exploration and potential advantages of MARL in public economics. A review article summarizing the application of AI in public economics indicates that the MARL algorithm roughly applied in the tax domain consists of four basic scenarios and the scope of the tax model is largely based on two basic types: general obligatory tax and VAT. This provides inspiration for further refining the research issues and modeling ideas in the optimal tax field.

In response to these research gaps, an ambitious plan to develop and validate a comprehensive conceptual framework that consists of modelling and optimization, interpreting and fairness checking, and comprehensive study and comparisons through coupling disciplinary synthesis is proposed. The explication and conceptual framework seek to facilitate the integration of AI with economic policy development and serve as a catalyst for a fuller understanding within academia and the wider communities concerned. The conceptual framework underscores the role of the knowledge connection between AI and economic development through the exploitation of data and recommender systems in economic and trade policy, financial strategy, and economic management, notably in the context of the emerging digital society and markets.

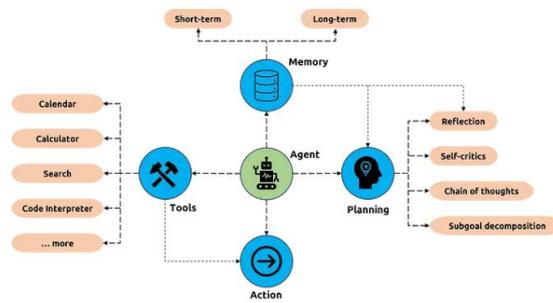


Fig 5: Agentic AI

5.1. Definition and Characteristics of Agentic AI

AI agency is not a myth, it is a reality of increasing socio technical importance. Though there are varying definitions, systems bearing the agency label have been developed and deployed. The public regularly encounters such systems but usually does not recognize them as such. It is imperative to catch up on how the “goals” of these systems influence events, impacting every sector. Thus agency is the focus: a system is regarded as agentic if it makes decisions that directly alter the trajectories of things in the physical world without human intervention. To that end, highly abstract, ‘may as well be magic’ AI interpretations of agency are avoided, opting instead for a concrete, technical definition that can be operationalized for rigorous examination.

There is a vision of deep artificial minds, a fantasy of AI Selfhood, that is categorically autonomous in an ungrounded, pseudo spiritual sense. While the discourse is dominated by an obsessive prediction, diagnosis does not fare better. Ironically, when put on the spot, most people have difficulty pinpointing the agency of some of the simplest, most notorious examples. The goal is to change that. A rapid increase in agency in commercial general purpose systems rivals attentiveness to the progression of spurious intelligence. Many applications involve difficulty discerning internally calculated instructions from luck or midstream collision either by happenstance or design. Agency is not the secret “magic” algorithm causing actions to mysteriously grow from data; it is something else happening in the system. Concerned parties deny being agentic. However, in subsequent discussions, many unwitting agents do take representation of their circumstances and intentions. AI agency has onerous responsibilities and maintaining an image of reliability is often incompatible with personal gain.

5.2. Role in Community-Centric Development

Modern financial services will be analyzed within mortgage financing. The prerequisites for community-centric curation will be laid out, and expert workshops together with suggestions for data sovereignty and decentralized funding models will be detailed. Research demands for transforming financial advisory with AI and data science will then also be laid out. An introductory analysis of best practices in community-centric development will moreover also be provided. Certain actors wish to accelerate the use of AI, big data, and data science in and the related digital transformation of the economy. Other actors emphasize the need to carefully consider the social implications of a growing reliance on this technology. Players like the insurance industry are instead thought by some to be able to assure a liability cover for entities involved in AI, big data, and data science. Similarly, insurance could possibly indemnify against the financial impact of fine or prosecution in cases of breaches of the regulation. One of the actors presents proposals to regulate AI. This regulation would cover among other things the sector, in particular for its civil liability rules.

Equ 3: Agentic AI Utility Function

- U : Agent utility
- a_t : Action taken at time t
- s_t : System state
- R : Reward function (e.g., increased inclusion)
- γ : Discount factor for future utility

$$U(a_t, s_t) = R(s_t, a_t) + \gamma \cdot \mathbb{E}[U(a_{t+1}, s_{t+1})]$$

6. Integration of Technologies

This article presents a framework or insight for AI and data-driven transformation in taxation, insurance, mortgage financing, and financial advisory services by integrating technological aspects with applications and impacts. The integrated technology for AI and data-driven transformation includes but is not limited to data processing and management, big data analytics, AI, blockchain, and their integrations. Key considerations for the data and AI-driven applications and their transformation in four service sectors are reviewed. Critically manufactured home is reviewed through the lens of multiple disciplines. It is examined from multiple perspectives, regulators, underwriters, home traders and buyers, and academic reviewers, engaging regulation and legislation, design, technology, finance and risk management. In general, purchasing of a manufactured home involves higher finance costs, and risk of financing damage repair to its foundation. A part of the scope in technology, finance, and regulation must be updated, appropriate for recent mobile/home ownership. Unfortunately, current technologies are considered necessary for examining the phenomenon of the focusing of the proposed research.

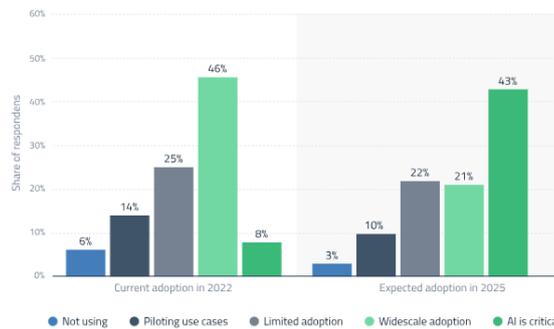


Fig : Artificial intelligence in finance

6.1. Interoperability of Cloud Computing and AI

This subchapter suggests a review and discussion on: (i) general technological trends forming AI-driven and data-driven transformation methodologies of standard tax calculations and control, insurance underwriting and advisory, bank and non-bank mortgage financing, and investment plans and financial advisory calculations; (ii) The technological infrastructure that supports these transformation methodologies; (iii) Analytical quantum mechanics of quantum point processes, concurrence, and maximum entropy; (iv) Standards developments or copyright-related efforts concerning these transformations.

6.2. Data Management and Governance

This section introduces a multidisciplinary framework for the research and practice of AI and data-driven transformation in taxation, insurance, mortgage financing, and financial advisory. A domain analysis explores agricultural finance, asset securitization, and bancassurance and M&A in accordance with tradition to diversify its perspective and to propose a potential complement. Domain-specific issues, such as accuracy of farmland values to address local economic policies, critical success factors in asset securitization for establishing a new finance platform, and threats in bancassurance and M&A to cultivate financial reinsurance products and destination strategies, etc.,

will be analyzed and discussed. General issues, including the need for a paradigm shift from human financing services to AI services and a call for an interdisciplinary field between finance and technology for joint research, will be explored. By providing a comprehensive view on AI and data-driven transformation, along with specific challenges and opportunities for potential future research, this multidisciplinary framework is expected to support a wide range of potential readers, including researchers, managers, and policymakers interested in the four domino industries.

7. Conclusion

This article expands upon a last Author's previous pieces and critics in a review. Since this is a brief report, illustrative use cases are preferred to be introduced at a later point. The framing and proposed multidisciplinary framework are based on discussions and feedback from professionals in the domains of tax authority, insurance, mortgage lenders, financial advisor, securities management, regulatory technology, as well as experts in technology development with various backgrounds.

AI model risk refers to the potential deviance of an AI model from expected monetary or social norms in negative ways, causing potential toxic websites, criminal conspiracies, and catastrophic events. Tax authorities and insurers become targets of AI system exploitation because of the latent asymmetric information that citizens/clients have less knowledge than these professional practitioners in these increasingly automated services. Regulating securities markets also calls for technology development to continuously screen systems that may conceal manipulative intentions or involve hidden agreements on a vast scale. On the other hand, properly regulated and accurately targeted AI models can also help entities on the same mission by matching transactions with diverse types of relevant public records, feeding back risk assessment with the generated explanation for both defending against potentially toxic accusations.

7.1. Future Trends

In this special issue, artificial intelligence and data-driven analytical models will be combined to solve contemporary taxation, insurance, mortgage financing, and financial advisory decision-making problems in an anti-fraudulent, fair, and transparent way, the four articles painting a global picture. The first article analyzes encryption tools by law enforcement agencies to access transactions in order to preserve financial secrets concerning mandatory tax audits. The second article proves that computer vision with deep learning and credit scoring models outperform the traditional approach by evaluating the lowest price technically acceptable. The third article shows that the automated valuation model improves and harmonizes property developer and lending officer expert judgments in the mortgage financing process, based on transactions. The last article describes a hybrid approach for psychologists and economists which outperforms either machine learning-based nudge strategies or expert human advisors, in terms of realized retirement-focused saver's latencies to achieve the pre-specified biologically plausible serotonergic concentration of the limited, highly addictive, and controlled substance.

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