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Are Artificial Intelligence and Machine Learning Shaping a New Risk Management Approach? The Impact for Italian Banks

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Abstract

Digital revolution is influencing many economic sectors and for a few years banking sector is under a great transformation mainly due to the development and the use of new technologies. The most recent ones are artificial intelligence (AI) with the recourse to advanced algorithms. The main banking services, their offer, but above all, the customer relations have been significantly influenced by the this. The recourse to new channels, the monitoring of risks and the controls of frauds are only some of the applications of machine learning (ML). To manage the increase in financial and non-financial risks AI and ML seem to give a great help to banks. The survey conducted from December 2022 to May 2023 with a sample of Italian banks of different size, shows the level of awareness in the recourse to these technologies. Moreover, it aims to assess the maturity and the future perspectives in the adoption of AI in the financial system. The analysis is divided into different investigation areas that show how banks can mitigate the risks involved with the implementation of AI and how it affects the risk management process. The paper covers the gap in literature where AI and ML are mainly considered as separate tools to face specific banking projects; and Italian banks, even if with differences due to the size, are aware of the relevance of these new technologies. The research is a contribute to the discussion about the application of AI and ML in a holistic dimension.

Keywords: artificial intelligence, banks, machine learning, risk management, financial sector

1. Introduction

The role of banks is relevant in a socio-economic system and its level of development is cause and effects of the financial growth of a country. The well-known functions of banks put in evidence that changes in their behaviour often imply a change in customers' habits. Banks support financial system with lending activity but also collect the savings form households; and in recent times their role in the payment services has become increasingly relevant. In the field of banking and financial services, however, recent technologies have disrupted the traditional activities and partially the banks' role, too, above all for the competition of new operators as Fintechs (Alt, Beck, & Smits, 2018). In a first stage it was internet to have a breakdown function with the development of online banking and the digitalization of services, but since a few years the real innovation is due to the use of artificial intelligence (AI) and machine learning (ML) in the financial sector, and in banking activity (Buchanan, 2019; Mahapatra & Singh, 2021). Even if banks are used to technology, the transition to AI and ML is implying a real innovative approach in the whole banking management: from customers' relationship to risk management, from new services' offer to platform of trading. The panorama of use and applications is wide, and the challenge is open in a more and more complex context.

An incentive to change towards a new banking model, innovative and technology compliant has also been required by customers themselves, above all by younger generations, more used to share their habits with technological devices requiring faster services, and thus, increasing the use of online and mobile banking. Therefore, banks are more and more interested in studying their customers, in following their behaviour to structure products to satisfy their exigences (Boukherouaa et al., 2021). This interest is solicited by the potentialities of managing a huge number of data and information (the so-called big data) thanks to the application of AI and ML, that not only grant the automation of banking activity, but are also able to overcome the limitation for the traditional statistical models used for data analysis. AI and ML can improve the economic results, increase revenues, and manage financial risks (Aziz & Dowling, 2019; Tammenga, 2020; Zetzsche, Arner, Buckley, & Tang, 2020). In fact, the digital transition in the banking sector is enhancing the customers' experience and decreasing the costs for the reduction of branches and other operative costs, improving the cost income ratio. The use of artificial intelligence and machine learning seems to be in the "nature" of banks that have always been prepared with a resilient approach, to accept new technological challenges, from the first introduction of computing machines to ATM, of these most evolved technologies.

In recent years the exponential growth of computing power and the availability of huge amount of data, are the main determining factors for the applicability of AI. This attention has been recently confirmed also at institutional level, through the proposal for a regulation, the "Artificial Intelligence Act", formulated by the European Parliament (European Parliament and the Council, 2021). The Act presents various protection measures to be adopted for the development, placing on the market and use of AI systems in the various sectors, with particular interest in those with high impact, including the financial sector. The banking system produces data with high information potential and is an important area for a fruitful use of the methods of AI and ML algorithms.

Identifying a universal definition of AI isn't easy as the discipline itself, and the studies dedicated to it, have been subject to multiple approaches and interpretations that have profoundly changed its meaning and characteristics over time. The field of AI research was officially born in the mid-fifties, when a group of US researchers met for the first workshop on AI organized by John McCarthy, in which some fundamental topics such as neural networks, computability theory and natural language processing were discussed (Boobier, 2020; Buchanan, 2019).

The term AI meant something different from the known "cybernetics" and had the aim of building "intelligent machines", capable of simulating every aspect of human intelligence (Boobier, 2020; Caron, 2019). However, many ideas that have contributed to characterize the discipline of AI already existed and, in this context, the most influential contribution in the field of computer science is due to Alan Turing, who outlined the problem of the recognizability of intelligence through behaviour without providing either an explicit definition or a practical application, but an empirical solution, with the so-called Turing test in 1950. Now the focus is to a renewed and increased interest in ML that allows to create systems that can improve their performance in certain activities, without having been specifically programmed through learning from data and experience (World Economic Forum, 2020).

Recently Hermann and Masawi (2022) put in evidence the evolution of AI from the simplest types where machines were only reactive and with limited memory, up to more complex types, able to use past experiences and historical data to make decisions, as happens in chat box or simulate human thinking with the ability of self-understanding. The increased use of AI in banking sector happened during the past decade, when banks discovered all the potentialities of AI and ML above all with the aim of fraud detection, but also of improving the efficiency and customer experience (Donepudi, 2017; Königstorfer & Thalmann, 2020). On the other hand, however, AI can cause new risks if not controlled. This happens when the system of AI gains much more power than human, or if ML lacks ethics, or causes legal risks, or inequalities and bias (La Torre, 2020; Sheedy & Lubojanski, 2018). These new risks must be considered in the whole scheme of risk management: for this reason, regulators and supervisors have put in evidence the relevance of cyber risks for financial intermediaries and banks, just for the large use of new technologies and an increased operativity on technological platform, opened to cyber-attacks (Fares, Butt, & Lee, 2022).

The introduction of AI into banking business model to manage information is an emerging field. In fact, AI solutions impact at a societal level with organizational and regulatory risks. For this reason, the analysis of AI's risks must be conducted on the basis of a multifaceted approach, as explained by Leo, Sharma, & Maddulety (2019).

The paper aims to consider AI as an opportunity only if its risks are taken under control. The actual literature is more focused on the consideration of AI to help banks in risk management, but our aim is to demonstrate that AI can define a new approach to risk management, not only for its models. The paper aims to cover the existing gap in literature about the use of AI, considering as valid a holistic vision of the problem (Boobier, 2020; Kou, Chao, Peng, Alsaadi, & Herrera-Viedma, 2019).

The adoption of the holistic vision implies the consideration of the Dynamic Risk Management Framework (DRMF) that has its origin in the analysis of specific industrial risks, but it can be considered a good theoretical background to enlarge AI influence on banking activity and on risk management process. The scientific fundament starts from the consideration that static risk analysis starts from the assumption that the probability distribution and its related parameters are fixed and remain fixed for the duration of the analysis. Static models cannot capture the time varying element or the uncertainty around the distribution parameters. They present a bi-dimensional views of the probability distribution. On the contrary a stochastic process can catch the time changing uncertainty into the analysis process. In this process the shape of a suggested probability distribution can change overtime because it can consider the uncertainty in the distribution parameters. Stochastic process or random process isn't a deterministic process, and it can encompass some uncertainty about the possibilities or probability distributions. A stochastic process uses times series and gives a three-dimensional view of the probability distribution. With a static forecasting environment, it is impossible to quantify the variability of the possible outcomes; on the contrary dynamic framework model can describe critical assumptions and their combined implications in terms of possible outcomes.

Therefore, the DRMF is different from the static risk management because it involves the simulation of the probabilities of risk events under uncertainty and it deploys feedback loops as preventative action if a risk event should appear. The preventative feedback actions are followed by new set of probability assessment and preventative actions. The purpose of the research is to investigate how AI can shape a new risk management approach in banking sector using DRMF that shows what banks are doing now in analysing risks, but above all the influence of AI implementation (Quell, Bellotti, Breeden, & Martin, 2021). The paper aims to offer a framework that can overcome the limitation of the actual models, by exploring how banks can mitigate risks with the DRMF.

The paper is based on a qualitative approach that uses a wide survey that has involved 359 Italian banks of different seize. The answers to the survey have been examined considering the size factors, as there are different approaches to risk management and the perception and the use of technology. With this analysis we aim to consider the AI and ML techniques and the impact areas, to identify the market position of banks and make suggestions for further research about some areas that aren't adequately covered. The survey covers specific thematic areas referred to structural functions of banks. The period of analysis goes form December 2022 to March 2023.

2. Literature Review

The present paper conceptually considers four areas also distinguished for the literature review. We maintain that the analysis of AI and ML as way for a new shaping of risk management in banks, can be divided into a) relevance of technology for the transformation of banking sector; b) risk management and AI, as moving factor and source of risk; c) different typologies of ML, as a part of AI; d) regulators' position about Ai in banking sector. The section is labelled in the same subsections.

2.1 Relevance of Technology for the Transformation of Banking Sector

As briefly indicated into the introduction to the paper, banking sector has been solicited to innovate since times. If we disregard the studies about the first technological innovation, the most recent boost to reshape banking industry has derived by Fintech that has disrupted banks' static, above all in payment services and credit supply (Alt, Beck, & Smits, 2018; Arner, Barberis, & Buckley 2017). Banks' innovation and technology have impacted the sector bringing changes at internal level, above all with a change in banking offer and services, pushing towards a customer centric relationship (Sanchez, 2022). Since 1990s banks have been managed on the basis of entrepreneurial principles and for this reason, they need to make a full budgeting analysis of their resources; technology helps them to reach the goal, because it is characterized by initial high investment, recovered in terms of successive management cost savings (K. Najaf, Mostafiz, & R. Najaf, 2021). The perspective of online banking, the reduction of physical branches and the improvement of the cost income ratio due to a decrease in operative costs have changed the banks' business models (Alonso, Berg, Kothari, Papageorgiou, & Rehman, 2020). Online and mobile banking have improved thanks to the evolution of banking technology (Singh, 2020; Thisarani & Fernando, 2021) and have led to fully digitalized reality where banks are fully substituted in all their services and operations by online experience for opening and using current accounts, receiving loans and consumer credits (Choi, Chan, Yue, 2017; Figini, Bonelli, & Giovannini, 2017).

Another effect of technological evolution of banks is the improvement of their efficiency, as best offer of financial services to customers according to their real exigences of place, time, and amount. To grant this satisfaction, banks must offer technical solutions adequate to customers concerning usability, customization, scalability, and security (Financial Stability Board, 2017). This means that the compliance with these aspects is a relevant constraint for a successful innovation strategy.

The digitalization, however, has also pushed banks to find new agreements and external collaboration. Partnership and outsourcing have been the policies adopted to compete with Fintech (Khandani, Kim, & Lo, 2010; Denœux, Dubois, & Prade, 2020; Alt, et al., 2018). Based on the dimension, other banks have also chosen the constitution of start-ups experiencing new forms of collaboration to offer more competitive products and better services (Caron, 2019).

As concerns the application of AI to various areas of banking activity, Boobier (2020) emphasises that financial sector is among the most affected by this technology. This is due to the availability of big data that can be explored thanks to AI analytics, that can give an in-depth analysis of customer behaviour, also improving risk analysis (financial and non-financial). ML shows also great potentiality and is the main factor of the actual restructuring of banking internal functions of back and front office (Singh, 2020; Aziz & Dowling, 2019). The main innovation relies on the creation of personalized user experience to predict purchasing behaviours; on the improvement of customer experience, useful to discover customers' needs deriving from their behaviour and their financial and non-financial habits; or on the application of virtual assistants based on AI that can support customers in their choices overcoming the limits of humans (working time, above all); or on the relevant fraud detection and risk management policy, aiming to reduce the impact of negative events due to suspicious transactions (Alonso et al., 2020; Boobier, 2020; Mehrotra, 2019; Buchanan, 2019).

In the field of investment and financial service Zetzsche et al. (2020) put in evidence the role of AI and technology. Roboadvisor can define personalized portfolios improving the results of the traditional statistical methods (IOSCO, 2021).

2.2 Risk Management and AI, as Moving Factor and Source of Risk

A bank ca be considered as a complex ecosystem and risk management must prioritize the in-depth study of business processes, activities, and assets. Only by understanding how each type of transaction takes place and how people interact with each other through the various business units, it is possible to map the probable weaknesses of the organization**.** In many cases, risks are not determined by external events, but they are the sum of procedural errors, pockets of inefficiency and incorrect approaches to productivity and operations. Mehrotra (2019) maintain that elements that, by stratifying themselves, cause accidents or reveal leaks, exogenous agents can affect through. Knowing these weaknesses means being able not only to calculate the probabilities with which, given certain critical issues, threats can occur, but also and above all to correct the problems (van Liebergen, 2017).

Such an approach, based on the logic of dynamic risk management, that we will consider further on, presupposes that each of the actors in the supply chains involved is responsible for reporting activities and process correction and execution of risk mitigation strategies (Caron, 2019; Chandrinos, Sakkas, & Lagaros, 2018). Therefore, to have an efficient process of risk management in banks it is necessary to involve the governance and the entire structure of the bank. Relying on a network that allows to exploit and make complementary the skills of each business unit to strengthen the defences both at a functional and at a systemic level, it's a need. The assignment of specific responsibilities to each resource is also essential to assign clear and well-characterized roles and operational areas in a clear and transparent way (Sheedy & Lubojanski, 2018).

It is almost obvious that the changes in banking activity have also impacted risk typologies. So, the risk classification in banks has enriched for typologies and effects. Financial risks still derive from the core banking, but they are also increased by other risks as cyber risks, due to digital transaction, or environment, social and governance (ESG) risks due to the hard implementation of these factors, or to their neglecting in some business. Moreover, also AI risks are present in the use of ML models where the typical "black box" question appears (Milojevic & Redzepagic, 2021). The classification of risks isn't static and fixed, and it is greatly influenced by the evolution of the operating context and the technological development of financial industry has reduced the steps in the relevance scale of risks: now, operative risk has almost the same importance of credit risk or other financial risks (Leo et al., 2019). The presence of several risk categories and/or subcategories does not necessarily mean a grade of relevance, above all if we consider the holistic dimension of banking activity (Embark, Haggag, & Saleh, 2022).

Even with new risk categories the steps for the risk management process remain (risk identification, risk measurement, risk control and monitoring and control) (Gunasilan & Sharma, 2022): banks define the actions that must put into practice to reduce the impact of risks. AI seems to offer specific support above all in specific categories of risks as credit risks, market, and liquidity risk (Addo, Guegan, & Hassani, 2018; Byrum, 2022; Devi & Batra, 2020; Jacobs, 2018). The support of AI and ML is focused on a more correct estimate of financial losses in credit risk analysis (Khemakhem & Boujelbene, 2017; Galindo & Tamayo, 2000; van Thiel & van Raaij, 2019); as concerns market risk (above all as interest rate risk and price risk) the aim is to control the potential losses associated with market fluctuations completing the traditional VAR and stress testing models (Kasztelnik, 2021; Heaton, Polson, & Witte, 2017).

As already mentioned with electronic banking and the adoption of new technologies and techniques in banking activity and for banking services, risks as reputational risks, legal and ethics risks, and strategic risks have added to risk management process (Fjeld, Achten, Hilligoss, Nagy, & Srikumar, 2020).

The specific consideration of ethics aspect of the use of AI has been considered by Caron (2019), but also faced by regulators (OECD, 2019a; OECD, 2019b; European Commission, 2020) and the "Artificial Intelligence Act" by European Parliament and the Council (2021) aims to control these aspects. In fact, the role of humans in AI adoption is a relevant topic, even to grant an equilibrate relation between humans and machines (Zetzsche et al., 2020; Boukherouaa et al., 2021).

Another role of AI explored in the field of risks is its applicability to control cyber threats. In fact, even if the technology itself can be considered as the source of cyber risk, it is also evident that AI-driven systems can identify details and different types of threats in short times (La Torre, 2020; Prenio & Yong, 2021). The real good functioning of AI-driven systems is however possible by considering only verified data (Thisarani & Fernando, 2021) and this result is possible, only if there is a human supervision for quality assurance of the data.

2.3 Different Typologies of ML, as a Part of AI

In literature AI represents the theory of computer systems able to have the same functions of human intelligence. ML is considered as a subcategory and ML is one of the methodologies used to over perform traditional statistical models in financial field (Aziz & Dowling, 2019; Dastile, Celik, & Potsane, 2020).

The advent of ML models is also due to the ability of these algorithms to extract value from the amount of data coming from the digitization and automation processes. Financial sector is characterized by data, constantly examined by statistics. For over a decade, the financial sector has been a particularly active driver for innovation in data analysis techniques (Angelini, di Tollo, & Roli, 2008). Trying to predict future scenarios and gain a competitive advantage is the key to creating value for the stakeholders of every banking institution. In financial sector, as data do not have linearity, statistical methods as linear regression present such limitation. ML methods can infer non-linear relationships. The key difference between ML and conventional econometric analysis is its larger focus on prediction compared to summarisation and causal inference (Varian, 2014). ML models can describe situations they have not seen before; it can learn from data and improve prediction (van Liebergen, 2017). For banks this means to define models that improve the control of default rates giving more reliable predictions.

Within the banking sector, the variables have a dichotomous nature determining two distinct behaviours. For example, for banks this is at the basis of the study of customer retention, necessary for the choice or not of a specific banking service. The advance identification of these customers or of this segment is a need for banks in the actual competitive scenario. In the past (Barboza, Kimura, & Altman, 2017), the rules for separating the two populations were based on Gaussian linear or quadratic approaches. In the linear approach it is assumed that the covariance matrix of the two populations is the same (this is equivalent to affirming, for example, that the variability of the characteristics of customers who have left the bank in the past are the same as those who have not) and that the two populations can be separated by a linear hyperplane.

A kind of generalization of this model is based on quadratic discriminant analysis that removes the hypothesis of equal variability between the two groups, preserving the hypothesis of normality. It is well known, however, that the distribution of variables in banking hardly follows the gaussian distribution. It is evident that one of the main objectives is to overcome these limits. The classification of ML methods is in favour of the possible solutions.

ML paradigms are the following three types: supervised, unsupervised and reinforcement and they are grouped on the basis of the learning mode.

In *supervised learning*, the algorithm learns from a set of labelled data, composed of past data with specific characteristics. The algorithm will learn a general rule for the classification (the model) and will predict the labels when new data are analysed.

With *unsupervised learning* the algorithms will learn from a dataset that does not have any labels and it will detect patterns in the data by identifying clusters of similar observations.

In *reinforcement learning*, the learning process of the algorithm derives from nteraction with the environment. The algorithm can choose an action starting from each data point collected analysing the environment and receives feedback indicating whether the action was good or bad. In this case the algorithm is trained by receiving rewards and 'punishments' and it adapts its strategy to maximise the rewards.

In financial sector it is possible to consider three macro-classes of supervised models:

- forecasting models: from Linear Regressions (LR) to sophisticated Temporal Fusion Transformers (TFTs), with main applications in trend forecasting, scenario simulation and monitoring of market and interest rate risks (Hamori, Kawai, Kume, Murakami, & Watanabe, 2018; Jung, Mueller, Pedemonte, Plances, & Thew, 2019);
- models for classification: from logistics functions to XGBoosts, with main applications in credit risk, rating production and assignment of risk levels (Addo et al., 2018; Angelini et al. 2008; Bono, Croxson, & Giles, 2021; Devi & Batra, 2020; Galindo & Tamayo, 2000);
- models for recommendation: from matrix factorizations to neural networks of various complexity: used especially in the operational and liquidity risk field (Kou et al., 2019; Tavana, Abtahi, Di Caprio, & Poortarigh, 2018).

In the case of unsupervised models, the algorithm tries to identify patterns within the data without being given a label or instruction by a human user. Rather, the correlations and spatial distances between points are calculated and the clusters are reorganized to reduce their entropy or otherwise minimize a loss function. The more data fed to the model, the more it can refine its ability to make decisions about the dataset.

This family of models includes:

- clustering models: useful for segmenting data into different groups such as customer types (CRO Forum, 2019);
- models for size reduction: useful to reduce the number of variables considered to find the needed information.

The lack of labelled data in banks brings to the choice of unsupervised or semi-supervised learning. The semi-supervised learning is also known as active learning because the algorithm identifies the most difficult data and asks the expert user to focus on labelling only these.

However, ML models haven't substituted statistical models yet; on the contrary they operate in a complementary way compared to traditional statistical methods. In general, although they maintain a predictive power of proven robustness, statistical models are especially suitable for detecting the relationships between the various variables involved, thus favouring interpretability. ML models, on the other hand, learn directly from data to make predictions and are very focused on performance, even in some cases against interpretability.

In the field of credit risk, using ML, ample opportunities are configured to improve risk forecasting performance, in all phases of the process of estimating, monitoring and validating models. Even the areas of application to risk parameters can therefore be the most diverse. Among the most relevant, in the first place, are those relating strictly to the modelling and quantification of traditional PD (rating), LGD and EAD risk parameters, both from an exclusively managerial point of view (with effects, for example, on credit provision processes, early-warning, quantification prudential provisions in an IFRS9 context and in Pillar II ICAAP optics, or other forms of stress testing), and with regulatory use purposes within IRB systems for the calculation of capital absorption against credit risk (Bonaccorsi di Patti et al., 2022; Orlova, 2020; van Thiel & van Raaij, 2019). Of particular importance is progressively being the use of ML solutions based on transactional data for the evaluation of customer affordability in the context of instant lending to household and small and medium enterprises (Addo et al., 2018).

Finally, applicability within early warning systems is of fundamental importance, where it is essential to improve the ability to manage credit deteriorations. For example, the effects on the income statement of higher provisions related to a greater slide in Stage 2 of performing customers according to IFRS9 can be considered. The objective variable of interest for the forecast is modified "anticipating" the default and the need for early detection of difficulties poses greater difficulty in identifying relevant *observable features*. Unsupervised *learning* techniques find space in the identification of relevant case studies, alternative models of different complexity and interpretability can be developed and compared to define functional solutions not only for predictive analysis of risk, but prescriptive of intervention actions.

However, it is evident that in the face of the increasing number and complexity of the drivers, the excessive "automation" of the processes in question, with the identification and selection of variables whose economic sense and relevance for the processes concerned are unclear, constitutes a potential risk itself. The role of sharing decision with the internal business structures must be absolutely preserved in every important phase of the selection process and rethought in the light of the increased loads and the changed complexity, otherwise the drift towards solutions are rejected in the application and / or poorly interpretable (Boukherouaa et al., 2021).

While sharing the concerns expressed by the regulator, it is evident, as mentioned, that an increasing adoption of

ML models for IRB models, will potentially produce an increase in the opportunities for adaptation and replacement of models, in a context – given the plurality of available techniques and areas and sub-areas of application – increasingly complex from the point of view of methodological skills necessary for their supervision and full understanding in evaluation.

2.4 The Regulators' Position about AI in Banking Sector

Technological changes have induced regulators to face the evolution of financial industry (Arner et al., 2016) and the application of technology to the regulatory framework (Guerra & Castelli, 2021; Truby, Brown, & Dahdal, 2020).

As concerns the regulation of AI itself, regulators and supervisors have focused on specific recommendation about AI and its applications, granting the respect of human rights, ethics and a one level playing field among countries (OECD, 2019b; European Commission, 2021a; European Commission, 2021b). The "Artificial Intelligence Act" (European Commission, 2021c) aims to be the regulatory framework not only in financial sector, but in a wider framework. In fact, the basic principle is to offer guidelines and minimum requirements about AI applications, safeguarding the global impact. AI is considered with its potentialities, but also with its risks.

For AI intelligence in financial sector EBA (2020) reported the level of applications for European banks and put in evidence together with IOSCO (2021) and Financial Stability Board (2017) the great expansion of ML models for all financial intermediaries. The phenomenon of open banking and open API requires a discipline in the use of common and interconnected data.

The peculiarities of ML models with the possibilities of biases and discrimination are at the basis of the need to overcome the "black box" phenomenon in which the "explainability" of a specific decision that the AI system makes must be prioritized (OECD 2019a; Bussmann, Giudici, Marinelli, & Papenbrock, 2021; Cascarino, Moscatelli, & Parlapiano, 2022). Another responsibility is referred to improve transparency and data privacy. Nevertheless, it urges to reach as soon as it is possible to a complete framework, in which AI and ML models find their discipline for financial industry, but also for society as a whole (Truby et al., 2020).

3. Method

The study is based on a qualitative approach using a survey submitted to a sample of Italian banks. The analysis is referred to consider the level of AI and ML adoption in banks' strategy and to evaluate the real condition of a new shape of management. The Dynamic Risk Management Framework (DRMF)seems to be appropriate to reach a control of risks through AI, considering a holistic dimension of banks of different size.

To collect qualitative data, the research has considered the results of a survey proposed to banks from December 2022 to March 2023. The study is based on an identified question, and this is confirmed by the relationship between existing theory and empirical findings. In fact, the empirical findings as results from the survey confirm the framework expressed by the examined literature.

The survey shows the banks' perspectives, and it is relevant as the state of art of Italian banks. We have considered the Italian banks as reported in the reference period December 2022, from the statistics of Bank of Italy, *Banks and financial institutions: branch networks*. The banks have been considered based on the classification by size. Bank of Italy ranks banks into five groups according to their size: major, large, medium, small and minor. In January 2022 the classification was updated using data on the average total assets for the three semesters comprising the second semester of 2020 and the second semester of 2021. The criteria used to place banks in one of the five groups were the following, as defined by Bank of Italy in its *Methodological Notes to Statistics*:

– major banks: average total assets greater than €60 billion;

– large banks: average total assets ranging from €26 billion to €60 billion;

– medium-sized banks: average total assets ranging from €9 billion to €26 billion;

– small banks: average total assets ranging from €1.3 billion to €9 billion;

– minor banks: average total assets less than €1.3 billion.

The Italian banks are as shown in Table 1.

Table 1. Banks by size (numbers in units)

Total Banks December 2022	Major banks	Large banks	Medium-sized banks	Small banks	Minor banks
439	8	12	19	143	257

Source: Bank of Italy, Banks and Financial Institutions: Branch Network, March 2023.

The overall number of banks and credits institutions in Italy decreased to 439 in 2022, from 740 in 2011. During the same period, the number of bank branches also decreased steadily because of the adoption of technology and the development of digital branches and online banks. In fact, the decreasing number of bank branches was not only due to the decrease in the number of banks and credit institutions, but also to the growing penetration of online banking, as well as the increasingly widespread use of banking apps via mobile devices. These aspects significantly contributed to the gradual loss of importance of physical branches. Moreover, also the Italian market have dealt with the challenge of the rise of new players in the banking sector: digital banks and financial services providers have caught the attention of many customers in the last few years.

The 439 banks are also exposed with their institutional category as shown in Table 2.

Table 2. Banks by institutional category (numbers in units)

Total Banks December 2022	Public limited banks	Cooperative banks	Mutual banks	Foreign banks
439	115	18	226	80

Source: Bank of Italy, Banks and Financial Institutions: Branch Network, March 2023.

From 439 banks have been excluded 80 foreign banks with a total of 359 banks that are the population of the analysis. Our sample of respondents is of 269 banks. The sample is constituted by the same proportion of all categories of banks by size. The survey has been conducted through online submission. According to the size and the internal organization each bank has sent the questionnaire to CEO, CRO, head of R&D office and/or head of the internal innovation hub.

The findings presented should be considered as an example of the adoption of AI and ML. This could be considered as a benchmark for future research and will stimulate debate.

4. Results

As explained in previous sections, the objective was that of considering the implementation level of AI applications and ML models in different business areas. For this reason the questionnaire was divided into the following thematic areas that are also the items of the research:

- AI for risk management,
- credit risk,
- financial risk,
- non-financial risk,
- governance.

The number of questions foreseen for each area of investigation was between 6 and 20, to provide an adequate representation of the state of the art at the system. Table 3 shows the questions divided on thematic areas and Appendix A contains the details of questions for each item with answers as percentage.

Table 3. Structure of the survey

Thematic areas	Items
AI for Risk Management	Can AI solutions significantly improve the profitability of the bank?
	What is the relevance of AI solutions in the strategic plan of the bank?
	What do you think is the framework in which AI solutions can bring the greatest benefits in banks?
	Do you think AI solutions are a determining factor for proper risk management?
	How would you define the relevance of AI solutions for risk management of your bank's specific strategic plan?
	What is the area of risk management that can most benefit from AI solutions?
	How long will it take to fully appreciate the benefits of AI solutions in risk management?
	Which is the main benefit of AI solutions to risk management?
	Which is the main obstacle to adopt AI solutions in risk management?
Credit Risk	Are there any credit risk initiatives that involve the use of AI solutions?
Financial Risk	Are there any financial risk initiatives that involve the use of AI solutions?
Non-Financial Risk	Are there any non-financial risk initiatives that involve the use of AI solutions?
Governance	Do you think that within your bank there are all the skills necessary for the design and implementation of AI solutions?
	Are the AI solutions in your bank built primarily using resources inside or outside the company?
	Is there a competence centre in your bank that supports risk management for initiatives involving AI solutions?
	Is this competence centre organisationally located under the risk management structure or under another structure?
	How would you define the organizational model that governs AI initiatives in your institution?

AI solutions are perceived as a competitive factor that can significantly improve banks' profitability regardless of the size of responding banks. The relevance of these solutions in the strategic plan varies depending on the size of the banks. As described in Appendix A there are two focus groups called major and minor banks that group banks by size. In fact, 40% of minor banks (according to Appendix A) declare that the relevance of AI solutions in the strategic plan is low, while 47% of major banks consider it high and 28% of major banks consider it very high. Among the possible areas of application of AI solutions, risk management is not considered in the first place. However, these solutions are still considered a key element for risk management. Customer interaction remains predominant as an area of application of AI solutions and goes beyond risk control as an area of application.

The scope with the greatest potential impacts is considered credit risk, followed by non-financial risk. The benefits of these impacts will be appreciable for minor banks in 5 years, while 40% of major and large banks believe the benefits are already evident. The main benefit related to the adoption of AI solutions is considered the improvement in quantitative risk assessment for major banks, although 30% of minor banks consider as an objective the greater effectiveness in continuous monitoring.

The resistance to change and performance of current analytical methodologies are considered among the main obstacles. Almost the same percentage of banks of the two groups declares the presence of AI initiatives in the credit risk field, mainly focused on improving the calculation of the PD, although it is possible to note for small and minor banks a strong interest in NPL management issues. Many of the solutions are in use but it is also possible to detect increasing adoption, given by the many pilot initiatives or under development. These initiatives are mainly applied in management for small and minor banks, while they also have a regulatory use for the other categories; 69% of banks declare the presence of AI initiatives in the financial risk area, in addition to credit risk and are essentially related to the areas of interest rate risk and liquidity risk.

60% of banks declare the presence of AI initiatives in the non-financial Risk sector, less widespread than credit risk initiatives. These initiatives are mainly focused on fraud management, although the number of ESG risk applications is significant.

Most banks believe that they have the internal expertise to develop AI solutions that are therefore preferably implemented with the use of internal resources. In 57% of major banks there are specialized competence centres for AI activities rarely placed under the structure of risk management. These banks operate mainly according to a "hub and spoke model", i.e. a hybrid organizational model that provides a pool of specialized resources at central level and dedicated resources that reside permanently in the individual organizational units. In particular, the "hub and spoke" model is present in 67% of major banks. In addition to the "hub and spoke model", the second most widely used operating model in small and minor banks is the distributed one, whose resources with AI and ML skills are distributed across all organizational units.

5. Discussion

Banks must deal with typical and new risks, from financial risks to non-financial ones, as reputational, operational, compliance, cyber and in general all risks deriving from changing customers' habits, from new technologies, AI and ML, among others. Risk management has become more and more relevant, but in the actual complex context the traditional risk management models seem not to be too adequate. They are structured to be regulatory compliant, instead of assessing risks continuously. The DRMF appears much more adequate ad it can improved by new data and new variables that present in banking activity and above all in customers' relationship. The use of AI and ML models offer the benefits of stochastic processes, that overcome the bidimensionality of static forecasting process at the basis of traditional risk management. The implementation of ML and AI helps banks in building a unique risk scoring methodology as management can use data from structured and unstructured sources. DRMF takes a holistic view as it is a continuous process using a deep learning-based network risk propagation model.

Italian banks' awareness of the importance of AI in their management overlooks bank's size and the increasing use of ML models for credit risk analysis and customer relationship needs an approach based on constant monitoring and on the analysis of all data deriving from customers' behaviour and habits. The DRMF is al regulatory compliant as banks can implement appropriate risk-based procedures.

To follow customers' profile DRMF is able to catch all those variables that the ML model capture as a consequence of customer information and customer's risk profile. The risk management system feed on various data and for this reason Italian banks have structured the hub and spoke system to offer AI and ML solutions. The new shape of risk management works well because all data (from structured and unstructured source) are used to create a unique risk scoring methodology and to apply AI-based predictive analytics for evaluating risks.

From the survey and the literature analysis it is evident that AI and ML, but in general, a series of technological support and the evolutions of statistical models towards stochastic processes, can improve risk management in banks. The use of big data in financial sector offers great potentialities to the financial sector.

We maintain that this research is a first step towards a holistic vision of banking activity and risk management. Further improvements are necessary. In our opinion the economic and financial benefits of this new shape of risk management should be investigated, to have a measure of the cost of risks and the revenues of its control.

The analysis hasn't considered an econometric model as other variables must be considered. In fact starting from the answers to questions, further analysis may consider:

- the improvement of the profitability of the banks measured through the selection of economic and financial ratios referred to items with positive answers;
- the reduction of specific risk typologies or variables after the adoption of AI solutions;
- the measurement of the effects due to different organizational models to implement or improve AI adoption.

The state of art of this sample of Italian banks may have interesting policy implications as they show the potential further applications. It is evident that the system is very different, and banks' size is one of the most discriminating variables. Also, the thematic area is relevant as some of them find the main use of AI, while others still remains partially covered and can be considered as the basin of future developments.

6. Conclusion

In recent years the greatest challenge for banks is the disruption due to new competitors and new technologies and techniques. The adoption at different levels of Ai and ML are a matter of facts. The survey to Italian banks presented in this paper supported by the literature and the relevance of the DRMF are a first step to understand the use of ML.

Even if there are different approaches among banks to these new technologies, the potential benefits and risks are evident. Ethics, privacy, and a complete regulation haven't yet a solution. The findings of this paper can be considered a basis for further exploration. We maintain to have contributed to research field by considering applicable to financial sector the DRMF, also thanks to the existence of the new technologies that give banks the opportunity to manage the customers' relationship, the risks, and the main managerial questions in a better way.

A first economic indicator of an improvement of the profitability of Italian banks is the value of the cost-to-income ratio. This ratio fluctuated significantly between 2014 and 2022. In the last quarter of 2022, the cost-to-income ratio was 59.03%, lower than the values observed in 2020 (68.26%) and 2021 (63.23%). This indicates that the cost of running operations became lower, therefore the profitability of Italian banking industry improved in the last couple of years.

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Appendix A

Details of questions and answers

As explained in section 3, the survey has involved Italian major, large, medium sized, small, and minor banks according to the size as defined by Bank of Italy. Notwithstanding in the structure of the survey two focus groups have been used: major and minor banks. Major banks include major, large and medium sized banks, while minor banks include small and minor banks.

Even if the sample was made of 359 banks, the respondents were 269 (5 major banks, 8 large banks, 11 medium-sized banks, 89 small banks and 156 minor banks).

Data are expressed as percentage and are reported for thematic area and item.

Thematic area: AI for risk management

Table A.1 Can AI solutions significantly improve the profitability of the bank?

	Yes	No	Don't know
All banks	86%	0%	14%

For this item the answers are independent from the size and they confirm the conviction of the adoption of AI solutions

Table A.2 What is the relevance of AI solutions in the strategic plan of the bank?

	Very high	High	Medium	Low
Major banks	28%	47%	13%	12%
Minor banks	0%	35%	25%	40%

Table A.3 What do you think is the framework in which AI solutions can bring the greatest benefits in banks?

Customer interaction	Market analysis	Risk Mitigation	Operations	Security
38%	13%	20%	10%	19%

Table A.4 Do you think AI solutions are a determining factor for proper risk management?

	Yes	No	Don't know
All banks	85%	5%	10%

Table A.5 How would you define the relevance of AI solutions for risk management of your bank's specific strategic plan?

	Very high	High	Medium	Low
Major banks	21%	42%	37%	0%
Minor banks	0%	28%	20%	52%

Table A.6 What is the area of risk management that can most benefit from AI solutions?

Credit Risk	Other Financial Risks	Non Financial Risks	Risk Integration
65%	20%	10%	5%

Table A.7 How long will it take to fully appreciate the benefits of AI solutions in risk management?

	Benefits already evident	In 1 year	In 5 years
Major banks	40%	28%	32%
Minor banks	10%	15%	75%

Table A.8 Which is the main benefit of AI solutions to risk management?

	Time saving	More effective risk factors identification	Improvement in quantitative risk assessment	Major granularity in customer's risk management	Major effectiveness in continuous monitoring	More efficient identification of corrective actions
Major banks	5%	10%	38%	25%	8%	14%
Minor banks	5%	25%	20%	10%	30%	10%

Table A.9 Which is the main obstacle to adopt AI solutions in risk management?

	High costs	Performance of current analytical methodologies	Resistance to change	Lack of company culture	Difficulty in communication between business, risk managers, modellers and IT resources	Future evolution of regulation
Major banks	10%	23%	28%	10%	19%	10%
Minor banks	13%	15%	30%	15%	20%	7%

Thematic area: Credit risk

Table A.10 Are there any credit risk initiatives that involve the use of AI solutions?

	yes	no
All banks	75%	25%

Table A.10.1 Breakdown of initiatives for different areas

	PD Calculation	LGD Calculation	EAD Calculation	NPL management
Major banks	42%	21%	19%	18%
Minor banks	40%	15%	15%	30%

Table A.10.2 Initiatives by regulatory or managerial use

	Regulatory	Managerial	Both
Major banks	25%	60%	15%
Minor banks	15%	72%	13%

Table A.10.3 Breakdown of initiatives by progress

	Under discussion	In development	Pilot	In use	Submitted to regulator
Major banks	8%	33%	13%	29%	17%
Minor banks	9%	28%	25%	30%	8%

Thematic area: Financial risk

Table A.11 Are there any financial risk initiatives that involve the use of AI solutions?

	yes	no
All banks	69%	31%

Table A.11.1 Breakdown of initiatives for different areas

	Market Data	Interest Rate Risk	Liquidity Risk	Pricing	Stress test/ ICAAP/ RAF	Other financial risks
Major banks	17%	30%	26%	10%	12%	5%
Minor banks	9%	28%	18%	9%	27%	9%

Table A.11.2 Initiatives by regulatory or managerial use

	Regulatory	Managerial	Both
Major banks	5%	28%	67%
Minor banks	9%	36%	55%

Table A.11.3 Breakdown of initiatives by progress

	Under discussion	In development	Pilot	In use	Submitted to regulator
Major banks	28%	22%	11%	37%	2%
Minor banks	11%	18%	9%	59%	3%

Thematic area: Non Financial risk

Table A.12 Are there any non-financial risk initiatives that involve the use of AI solutions?

	yes	no
All banks	60%	40%

Table A.12.1 Breakdown of initiatives for different areas

	Loss Data Collection	Scenario analysis	Fraud Risk	ICT risk and Cyber security	ESG risks	Other risks
Major banks	15%	12%	23%	20%	25%	5%
Minor banks	8%	7%	38%	25%	18%	4%

Table A.12.2 Initiatives by regulatory or managerial use

	Regulatory	Managerial	Both
Major banks	5%	40%	55%
Minor banks	4%	55%	41%

Table A.12.3 Breakdown of initiatives by progress

	Under discussion	In development	Pilot	In use	Submitted to regulator
Major banks	16%	15%	10%	55%	4%
Minor banks	5%	7%	8%	78%	2%

Thematic area: Governance

Table A.13 Do you think that within your bank there are all the skills necessary for the design and implementation of AI solutions?

	yes	no
All banks	67%	33%

Table A.14 Are the AI solutions in your bank built primarily using resources inside or outside the company?

External resources	Internal resources	Resources equally divided between internal and external
14%	36%	50%

Table A.15 Is there a competence centre in your bank that supports risk management for initiatives involving AI solutions?

	yes	no
Major banks	57%	43%
Minor banks	48%	52%

Table A.16 Is this competence centre organisationally located under the risk management structure or under another structure?

	Risk Management	Another structure
All banks	37%	63%

Table A.17 How would you define the organizational model that governs AI initiatives in your institution?

	Centralized model	Distributed model	Hub and Spoke	Other type of organizational model
Major banks	0%	17%	67%	16%
Minor banks	12%	38%	50%	0%