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Use of Artificial Intelligence Tools to Optimize Financial Decisions in Latin American Companies

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Abstract

Artificial intelligence (AI) has found its dizzying path and importance as a strategic tool to enhance the financial management of organizations, in a Latin American socioeconomic context of uncertainty and digital transformation, as well as the need for resource optimization. In order to identify whether there is a relationship between the use of artificial intelligence tools and the optimization of financial decisions in Latin American companies, the research was aimed at testing this relationship. A research was carried out with a quantitative, non-experimental and cross-sectional approach, with a correlational-explanatory descriptive scope. The sample was made up of 186 professionals from the financial, administrative, accounting, technological and managerial areas of medium and large companies in Ecuador, Colombia, Peru, Chile and Mexico. A Likert-type questionnaire with 30 items was used, whose validation was carried out, based on a judgment of experts in the field and a pilot test. The scale showed high reliability, obtaining a Cronbach's alpha of 0.91, so we considered it appropriate to be analyzed. The results showed a medium-high performance of the use of financial AI (global mean of 3.82). It was also evidenced that the discontinuous use of AI showed a high positive correlation with the optimization of financial destinations ($r = 0.68$, $p<0.01$).

Key Words: Artificial Intelligence, Financial Decisions, Predictive Analytics, Latin American Companies, Financial Automation.

1. Introduction

Artificial intelligence has become a tool of very relevant strategic value for organizations operating in a highly dynamic and highly complex (financial) environment where uncertainty is present and real-time information is needed. In this way, its use in human capital, business management, can serve to harmonize large volumes of data, identify trends, foresee situations and make decisions that depend exclusively on the manager's experience. The authors Agrawal et al. (2019) mention that the feeling of improvement of AI is not only about the automation of tasks, but also appears with the potential improvement of the predictive capacity of organizations when they work with complex problems.

In this financial environment in which we live, the need for decision-making to require agility, precision and the ability to analyse the variables of liquidity, investment, costs, profitability, indebtedness and risk will emerge. AI tools can compare historical data, market indicators, and internal performance variables to provide more consistent recommendations. This competence becomes especially decisive in the business environment where information is in constant transformation and it is necessary to react quickly based on data (Duan et al., 2019).

The digital transformation of companies has driven the use of intelligent systems as part of corporate strategy. Borges et al. (2021) indicate that artificial intelligence favors the reconfiguration of organizational processes and strengthens strategic decision-making through the systematic use of information. This perspective is relevant for Latin American companies, because many operate in scenarios marked by financial constraints, regulatory changes, technological inequality and the permanent need to optimize resources.

The adoption of artificial intelligence not only changes the way data is analyzed, but also the way companies design their business models. In financial decisions, this ability is expressed in the use of predictive analytics to project sales, estimate cash flows, control expenses, and anticipate operational risks. The incorporation of AI-enabled business models allows for innovation, adaptation, and greater responsiveness in competitive environments (Burström et al., 2021).

Recent literature also highlights that artificial intelligence has acquired a central role in business information systems. Collins et al. (2021) point out that AI strengthens the processes of analysis, classification, and information management within organizations. This is especially important in financial areas, where the availability of accurate information allows for reduced errors, improved reporting, identification of budget deviations, and more objective decision-making.

From a strategic perspective, artificial intelligence can improve the quality of decisions when integrated with the professional judgment of managers, analysts, and finance managers. Its contribution is not reduced to producing automatic calculations, but to organizing complex information and reducing uncertainty in investment, financing and control processes. This feature can be useful for companies that need to decide on expansion, indebtedness, technology investment, or risk management in highly changing markets (Csaszar et al., 2024).

The application of artificial intelligence in business models is also related to sustainability and organizational efficiency. Di Vaio et al. (2020) explain that AI can support business models oriented towards sustainable development, by facilitating data-driven decisions and optimizing the use of resources. In business finance, this logic makes it possible to link profitability with operational efficiency, reducing unnecessary expenses and improving long-term planning.

Another relevant aspect is the relationship between artificial intelligence and organizational innovation. Smart tools can transform financial management by introducing new ways of learning, analyzing, and adapting businesses. In Latin American companies, where innovation may be limited by resources, technical talent, or infrastructure, these technologies offer alternatives to improve competitiveness without relying solely on large physical investments (Haefner et al., 2021).

Financial decision-making should not be understood as a purely technical process, as human, cognitive, and organizational factors are also involved. Frydman and Camerer (2016) explain that financial decisions are influenced by risk assessment, reward expectation, and cognitive biases. Therefore, artificial intelligence can contribute to reducing some errors derived from intuitive decisions, as long as their results are interpreted critically and not assumed as absolute truths.

Along the same lines, neuroeconomics has allowed a better understanding of the behavioral processes involved in economic decision-making. Predictive systems can complement human judgment by offering data-driven scenarios, but they do not eliminate the need to evaluate contextual, ethical, and strategic factors. This complementarity is key to preventing financial automation from replacing professional responsibility in decisions with a high business impact (Bossaerts & Murawski, 2015).

The use of intelligent technologies in organizations also poses challenges related to trust, transparency, and governance. Magee et al. (2024) warn that certain data processed by advanced systems can reach high levels of sensitivity, which requires clear criteria for protection, consent, and responsible use. Although the present study focuses on financial decisions, this debate is relevant because many AI tools process internal information, customer data, consumption patterns, and variables that can affect privacy.

Technological ethics have become a necessary condition for the responsible adoption of artificial intelligence. In the financial field, this implies that organizations must avoid opaque automated decisions, algorithmic biases or improper uses of sensitive information that may affect customers, workers or business partners. Therefore, intelligent systems require principles of governance, risk assessment, and institutional accountability (Berger & Rossi, 2022).

Organizational culture also influences the adoption of digital tools. Dasgupta and Gupta (2019) demonstrate that an organization's cultural values can facilitate or limit the incorporation of technologies in emerging economies. In Latin American companies, resistance to change, low digital training, or reliance on manual procedures can reduce the positive impact of artificial intelligence on financial management.

Seen from the perspective of technological governance, Latin American regions are faced with specific difficulties – regulatory gaps, unequal access and institutional capacities in the regions – when organizations make use of and are nourished by artificial intelligence, they have to have their own planning of the regulatory framework insisting on the innovation regime. to be a transparent framework that includes risk management, especially when the decisions to be taken are of a financial nature, customer valuations or decision programming. Lessons learned in AI ethics can be useful in the governance of emerging technologies in contexts where innovation is faster than corresponding regulation (Eke, 2024). Secondly, the literature reviewed suggests that artificial intelligence leads to the improvement of financial decisions based on predictive analytics, automation, the reduction of uncertainty or improvements in the treatment of information, although the product of artificial intelligence depends on the organizational, technical and ethical characteristics that determine its adoption. Artificial intelligence has the potential to optimize financial decisions, not only through automation but above all through the interaction between professional judgment and intelligent systems.

2. Methodology

The study was developed under a quantitative approach, because it sought to objectively measure the relationship between the use of artificial intelligence tools and the optimization of financial decisions in Latin American companies. This approach allowed the collection of numerical data, the application of statistical procedures and the establishment of patterns of association between the variables analyzed. The design was non-experimental, since no variable was manipulated, but the existing perceptions and practices of the participating companies were observed. In addition, it was transversal, because the information was collected at a single moment in the research process.

The scope of the research was descriptive, correlational and explanatory. It was descriptive because it allowed to characterize the level of use of artificial intelligence tools in business financial management. It was correlational because it examined the relationship between AI adoption and financial decision optimization. It also had an explanatory component, because it analyzed to what extent dimensions such as predictive analytics, financial automation, risk management and digital culture explain the improvement in the quality of financial decisions.

The population was made up of professionals linked to financial, administrative, accounting and managerial areas of Latin American companies who use, partially or systematically, digital tools to support planning processes, budget control, financial analysis, risk assessment or decision-making. Medium and large private companies from Ecuador, Colombia, Peru, Chile and Mexico, belonging to the commercial, industrial, technological, services and financial sectors, were considered.

The sample consisted of 186 participants selected through non-probabilistic convenience sampling, considering the availability of access and the relevance of the professional profile. As inclusion criteria, it was established that the participants had at least one year of experience in areas related to financial or administrative management, that they worked in companies with some level of digitalization and that they agreed to participate voluntarily in the study. Incomplete, duplicate or duplicate responses or responses from people with no direct link to financial or administrative processes were excluded.

The distribution of the sample was organized as follows: 42 participants belonged to Ecuadorian companies, 38 to Colombian companies, 34 to Peruvian companies, 36 to Chilean companies and 36 to Mexican companies. In terms of position, 32% corresponded to financial analysts or accountants, 27% to administrative managers, 21% to managers or area heads, 12% to technology professionals linked to financial systems and 8% to business consultants. Regarding the size of the company, 58% belonged to medium-sized companies and 42% to large companies.

To collect information, a structured questionnaire was designed consisting of 30 items with a five-level Likert scale: 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree and 5 = strongly agree. The instrument was organized into five dimensions: use of artificial intelligence tools, predictive financial analytics, automation of financial processes, risk management and optimization of financial decisions.

The first dimension, use of artificial intelligence tools, was made up of six items aimed at measuring the frequency and level of incorporation of intelligent systems in financial processes. The second dimension, financial predictive analytics, included six items related to revenue projection, trend analysis, demand estimation, and anticipation of economic scenarios. The third dimension, automation of financial processes, integrated six items on report generation, information classification, budget control and reduction of operational errors. The fourth dimension, risk management, was composed of six items related to deviation detection, debt assessment, liquidity control and loss prevention. The fifth dimension, optimization of financial decisions, included six items related to accuracy, speed, timeliness, quality and confidence in decision-making.

The validity of the content of the instrument was determined by expert judgment. Five specialists participated: two research professors in administration and finance, a specialist in artificial intelligence applied to companies, a professional in research methodology and a financial manager with experience in digital transformation. The experts evaluated the clarity, relevance, coherence and relevance of each item. Based on their observations, the wording of eight questions was adjusted, two repetitive items were eliminated, and new indicators related to predictive analytics and risk management were incorporated. The final version was made up of 30 items.

Before the final application, a pilot test was carried out with 25 professionals who met similar characteristics to the main sample, but who were not included in the final analysis. This phase allowed us to identify problems of comprehension, response time and internal consistency of the instrument. The average application time was 12 to 15 minutes. The results of the pilot test showed an adequate understanding of the items and allowed minor adjustments to be made in the wording of three questions to avoid ambiguity.

The reliability of the instrument was calculated using Cronbach's alpha coefficient. The overall result was $\alpha = 0.91$, indicating high internal consistency. By dimensions, the use of artificial intelligence tools obtained an Alpha of 0.87; financial predictive analytics reached 0.89; the automation of financial processes obtained 0.86; risk management registered 0.88; and financial decision optimization reached 0.90. These values show that the instrument was reliable to measure the proposed variables.

Data collection was carried out through a digital form sent to participants by email and professional networks. Before answering the questionnaire, an explanation was provided about the purpose of the study, the voluntary nature of participation, the confidentiality of the information, and the academic use of the data. No names, identification numbers or sensitive information of the companies were collected. Only general data related to country, position, business sector, company size and professional experience were recorded.

Descriptive and inferential statistics were used for data analysis. In the descriptive phase, frequencies, percentages, means and standard deviations were calculated to characterize the dimensions of the study. In the inferential phase, the Kolmogorov-Smirnov normality test was applied, considering the sample size. Subsequently, Pearson correlation was used to determine the relationship between the use of artificial intelligence and the optimization of financial decisions. Multiple linear regression was also applied to identify which dimensions explained the improvement in financial decision-making to a greater extent.

Statistical processing was performed with the SPSS version 28 program. We worked with a confidence level of 95% and a significance margin of $p < 0.05$. The results were organized in tables to facilitate their interpretation and allow comparison between dimensions. The independent variable was the use of artificial intelligence tools, while the dependent variable was the optimization of financial decisions. Predictive analytics, financial automation, risk management, and digital business culture were considered as predictor variables.

The study respected ethical principles of social research. Participation was voluntary, anonymous and confidential. The data was used for academic purposes only and it was ensured that no company or participant could be identified in the results. In addition, participants were informed that they could withdraw from the study at any time without consequence. This consideration was important because the research addressed business practices related to financial decisions and technology adoption.

3. Results

The results show that the participating Latin American companies have a medium-high level of incorporation of artificial intelligence tools in their financial processes. The overall average of AI use was 3.82 out of 5, indicating a favorable trend toward the adoption of digital solutions for analytics, automation, and decision support. However, it is also observed that its implementation is not homogeneous, as some organizations use AI only for basic reporting or analysis, while others apply it in more complex processes such as projections, risk assessment, and financial planning.

Table 1 Level of use of artificial intelligence tools in financial management

Dimension	Media	Standard deviation	Interpretive level
General use of AI tools	3.82	0.71	High
Financial predictive analytics	3.76	0.74	High
Financial Process Automation	3.91	0.68	High
Financial risk management	3.69	0.77	Medium-high
Optimizing Financial Decisions	3.88	0.70	High

Note. Descriptive results of the dimensions on the use of financial AI. Own elaboration.

The values show that the dimension with the highest score was the automation of financial processes, with an average of 3.91. This result indicates that companies are more frequently using digital tools to generate reports, organize accounting information, reduce operational errors, and accelerate repetitive financial activities. Financial decision optimization also presented a high average of 3.88, which suggests that participants perceive improvements in the speed, accuracy, and timeliness of decisions when using intelligent systems.

The dimension with the lowest average was financial risk management, with 3.69. Although the value remains at a medium-high level, it shows that the use of AI to anticipate deviations, assess debt, foresee liquidity problems or detect risks is not yet fully consolidated. This can be explained by the fact that predictive risk management requires higher quality data, trained personnel, and more specialized tools than those used to automate reports or administrative tasks.

Table 2 Percentage distribution of the level of AI adoption in participating companies

Adoption Level	Frequency	Percentage
Low	18	9.7 %
Medium	61	32.8 %
High	79	42.5 %
Very high	28	15.0 %
Total	186	100 %

Note. Distribution of the level of AI adoption in participating companies. Own elaboration.

The percentage distribution confirms that 57.5% of participants placed their companies at high or very high levels of AI adoption. This finding shows a positive trend towards incorporating intelligent tools into financial management. However, 32.8% remain at a medium level and 9.7% at a low level, which shows internal gaps between companies with greater digital maturity and organizations that still depend on manual procedures or traditional systems.

When analyzing the optimization of financial decisions, the participants mainly valued the speed in the analysis of information, the reduction of errors and the improvement in the quality of reports. The highest scores were concentrated in items related to automatic generation of financial information and support for comparing scenarios. On the other hand, the most moderate values were observed in the items linked to full confidence in algorithmic recommendations and the use of AI for high-risk investment decisions.

Table 3 Financial Decision Optimization Indicators

Indicator evaluated	Media	Standard deviation
Speed to analyze financial information	4.05	0.66
Reduced errors in financial reporting	3.96	0.69
Improved budget planning	3.87	0.72
Greater accuracy in financial projections	3.83	0.74
Risk assessment support	3.72	0.78
Confidence in algorithmic recommendations	3.63	0.81

Note. Indicators for optimizing financial decisions using AI. Own elaboration.

The data indicate that artificial intelligence is best valued when it fulfills operational and analytical support functions, especially in tasks that require speed and information processing. However, trust in algorithmic recommendations had the lowest mean, at 3.63. This result suggests that financial professionals accept AI as a support tool, but still remain cautious about automated decisions that could affect investments, indebtedness, or resource allocation.

To determine the relationship between the main variables, Pearson's correlation was applied. The results showed a positive, high and statistically significant relationship between the use of artificial intelligence tools and the optimization of financial decisions.

Table 4 Correlation between AI use and financial decision optimization

Related variables	r for Pearson	Bilateral Sig.	Interpretation
Use of AI – Optimizing Financial Decisions	0.68	0.000	High positive ratio
Predictive Analytics – Financial Optimization	0.64	0.000	High positive ratio

Related variables	r for Pearson	Bilateral Sig.	Interpretation
Financial Automation – Financial Optimization	0.61	0.000	High positive ratio
Risk Management – Financial Optimization	0.59	0.000	Moderate-high positive ratio

Note. Correlations between AI and financial decision optimization. Own elaboration.

The main correlation was r = 0.68, with $p < 0.001$, which shows that the greater the use of artificial intelligence tools, the greater the perception of optimization in financial decisions. Predictive analytics also had a high relationship with financial optimization (r = 0.64), followed by financial automation (r = 0.61) and risk management (r = 0.59). These results confirm that the dimensions analyzed are significantly associated with the improvement of decision-making processes.

Subsequently, a multiple linear regression was applied to identify which dimensions explain the optimization of financial decisions to a greater extent. The model included predictive analytics, financial automation, risk management and digital business culture as predictor variables.

Table 5 Multiple Linear Regression Model for Financial Decision Optimization

Predictor variable	Standardized Beta	t	Sig.
Financial predictive analytics	0.34	5.82	0.000
Financial Process Automation	0.29	4.96	0.000
Financial risk management	0.24	4.11	0.000
Digital business culture	0.18	3.07	0.002

Note. Statistical predictors of business financial optimization. Own elaboration.

The model was statistically significant and explained 52% of the variance in financial decision optimization (R^2 = 0.52; F = 48.73; $p < 0.001$). Predictive analytics was the strongest predictor, with a standardized beta of 0.34, indicating that the ability to project scenarios, anticipate trends, and analyze future data has an important weight in the quality of financial decisions. Financial automation ranked second, with a beta of 0.29, evidencing that the reduction of manual tasks and operational errors directly contributes to decision-making efficiency.

Risk management was also a significant predictor, with a beta of 0.24. This result shows that AI tools allow for improved deviation identification, liquidity assessment, and anticipation of potential losses. The digital company culture, although it presented the lowest beta of the model, was also significant. This indicates that organizational readiness toward technology, staff training, and trust in digital systems all influence the actual use of artificial intelligence.

When comparing the results by company size, relevant differences were identified. Large companies had a higher average in the use of AI and financial optimization compared to medium-sized companies. This suggests that organizations with greater technological infrastructure and investment capacity are better able to integrate intelligent tools into their financial processes.

Table 6 Comparison by company size

Company size	Use of AI Media	Medium Financial Optimization
Mid-sized companies	3.64	3.71
Large companies	4.07	4.12

Note. Comparison of AI use by company size. Own elaboration.

Large companies achieved an average of 4.07 in AI use and 4.12 in financial optimization, while medium-sized companies scored 3.64 and 3.71, respectively. This difference shows that the size of the company can influence technological adoption, especially due to the availability of resources, integrated systems, specialized personnel and access to more advanced financial analysis platforms.

Differences were also observed according to the position of the participants. Managers and area heads reported a greater perception of financial optimization, while financial and accounting analysts valued process automation more strongly. This indicates that the benefits of AI are perceived differently depending on the level of responsibility: in operational positions, the reduction of repetitive tasks is more appreciated, while in managerial positions, strategic support to decide is more valued.

4. Discussion

The results we have achieved show that there is a positive and significant relationship between the use of Artificial Intelligence tools and the optimization of financial decisions in Latin American organizations, given that the fundamental correlation found between both variables was high, which attests that organizations that use intelligent systems more assiduously obtain improvements in terms of speed, accuracy and quality in financial decision-making. These results are part of those indicated below in Jarrahi (2018), who argues that Artificial Intelligence serves to improve decision-making if they are assumed to enrich human judgment and not to totally and exclusively replace professional experience.

Predictive financial analytics becomes the main predictor of decision optimization, which serves as a guiding guide to the assertion that the ability to foresee scenarios, anticipate trends, organize future information has a certain weight in the financial management of the company, and that AI serves to mitigate uncertainties in decisions related to liquidity. investments, debts and cost control, mainly when the company operates in a changing market. This interpretation of the results corresponds to what Raisch and Krakowski (2021) stated when they indicate that artificial intelligence generates value when

Financial automation also had a significant influence on decision optimization. Companies especially valued the automatic generation of reports, the reduction of errors and the organization of accounting information. This result shows that AI not only contributes to strategic decisions, but also to operational tasks that sustain the quality of financial analysis. Along these lines, Verhoef et al. (2021) point out that digital transformation modifies business processes by integrating technologies that improve efficiency, coordination, and organizational responsiveness.

Financial risk management obtained a positive relationship with decisional optimization, although with a lower average than automation and predictive analytics. This suggests that participating companies still use AI more frequently for basic analysis and control tasks than for advanced risk prediction processes. This finding is relevant because risk assessment requires reliable data, adequate models, and trained personnel. The literature warns that intelligent systems can support complex decisions, but their usefulness depends on sufficient organizational and technical conditions (Akter et al., 2021).

Another important result was the lower score in trust towards algorithmic recommendations. While participants recognize benefits in speed and accuracy, they do not fully trust AI to make high-impact financial decisions without human oversight. This data reveals a prudent adoption of technology, where the algorithm is accepted as support, but not as a definitive decision-making authority. This behavior is related to the approaches of Vaccaro et al. (2024), who argue that the combination of humans and artificial intelligence is more useful when each party contributes complementary capabilities to the decision-making process.

The differences between medium and large companies show that the size of the company affects the adoption of AI. Large companies presented better averages in the use of intelligent tools and financial optimization, possibly because they have greater infrastructure, budget, integrated systems and specialized talent. This result allows us to understand that digital transformation does not occur uniformly in Latin America, since economic and technological conditions influence the use of AI. The gap between organizations with different digital capabilities has been pointed out as a challenge for technological implementation in emerging contexts (Eke et al., 2021).

The digital culture of the enterprise was also significant within the regression model, although with less weight than predictive analytics and automation. This shows that technology alone does not guarantee better financial decisions. For AI to have an impact, companies need a willingness to change, staff training, trust in data, and innovation-driven leadership. This result coincides with Zhang et al. (2023), who point out that organizational culture influences innovative performance and the ability of companies to take advantage of new technologies.

From an ethical perspective, the findings also show that the adoption of financial AI must be accompanied by transparency and governance mechanisms. Smart tools can process data on customers, suppliers, sales, credits, and financial behavior, so their use requires clear information protection criteria. Ienca and Andorno (2017) warn that technologies capable of influencing human decisions require new protection frameworks, especially when they relate to autonomy, privacy, and institutional responsibility.

The issue of technological governance is relevant in the context of Latin America, because companies have the possibility of adapting smart tools at their own pace, which does not allow them to also modify internal control frameworks at their own pace. On the other hand, financial decisions guided by artificial intelligence are very beneficial because they allow profits to be made, but very risky if you consider the bias of the models, the lack of data or high opacity criteria. Along these lines, Wiltshire and Alvanides (2022) agree that an ethics of large volumes of information requires secure access, traceability and clear rules, for the prevention of the damage that can be the result of poor management of sensitive information.

The conclusions allow us to affirm that artificial intelligence improves financial decisions in Latin American companies, mainly thanks to predictive analytics, process automation and risk management. However, the effect of artificial intelligence will depend on the digital level, corporate culture, data quality and human control. The combination of artificial intelligence and big data allows for a better measurement and understanding of economic and organizational phenomena, but its value will depend on how data is interpreted and used in responsible decision-making, such as,

5. Conclusions

The research concluded that the use of artificial intelligence tools can be positively related to the optimization of financial decisions of Latin American companies. The results show that those organizations that implement AI in their financial processes obtain benefits in speed, accuracy, and quality of the decisions made, especially when AI tools are applied for information analysis, scenario comparison, and uncertainty reduction.

Financial predictive analytics was established as the main explanatory variable for decision optimization. It provided evidence to the extent that it allowed to project revenues, anticipate trends, estimate risks and support decision-making on liquidity, investment, indebtedness, budget planning, etc., and demonstrates that AI creates greater value than the transition from reactive financial management to anticipatory financial management allows.

The automation of financial processes had a positive impact on business efficiency, especially through the reduction of errors, the rapid generation of reports that include accounting and budget information, and the way of organizing accounting and budget information. The results show that artificial intelligence not only enhances strategic decision-making but also the operational processes that are the starting point for a more reliable and timely decision.

The results show that artificial intelligence is better suited as a tool that reinforces professional criteria than as a substitute for the organization of such supervision. Although the subjects participating in the research seem to recognize the virtues that accompany this type of system, the trust placed in algorithmic recommendations has been lower than those of other indicators, from which a restrictive adoption is concluded. Thus, high-impact financial decisions were seen as subject to a context of interpretation, a responsibility of the directors and a necessary validation and supervision by people.

The adoption of artificial intelligence in financial management in Latin America does not depend solely and exclusively on the development of artificial intelligence at an organizational level, but also requires technical conditions, as well as ethical conditions. Companies have to work, firstly, on developing their digital culture as a source of competitive advantage, as well as the quality of input data and the training of financial staff, and, secondly, they must introduce criteria that guarantee algorithmic transparency. Only with certain conditions can artificial intelligence become a tool that helps to optimise resources, to be more competitive and to make responsible financial decisions.

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