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INTERPRETING THE QUALITY OF INFORMATION AND THE ROLE OF ARTIFICIAL INTELLIGENCE IN CORPORATE DECISION–MAKING

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Abstract: The relationship between corporate performance and the quality of utilized information has long been a focal point of research. Numerous studies confirm that high–quality information enhances competitiveness and positively influences decision–makers' effectiveness: reliable data increases the likelihood of rational and efficient decisions. Nevertheless, acquiring real, relevant information often faces obstacles, and current practices in managing information quality remain insufficient. The use of information is not merely a quantitative issue; relevance and context are also critical. According to Ackoff's (1967) seminal study, most managers suffer not from a lack of information but from an overload of irrelevant or misleading data, which hinders effective decision–making. This study seeks to answer how artificial intelligence (AI) can help overcome these challenges. A key objective is to present the potential applications of AI in information processing and analysis. This article is based on the doctoral dissertation of one of the main author. However, the timeliness of the topic and the rapid advancement of artificial intelligence (AI) necessitated complementing the original findings with AI–related insights.

Keywords: AI, information value, information interpretation, corporate resource

INTRODUCTION

Traditional approaches assume the availability of high–quality information, but in practice, determining and utilizing the factual content of information poses significant challenges for corporations. Current models (e.g., microeconomic frameworks) assume the objectivity of information but lack methodological tools to verify their factual accuracy. To address this gap, we introduced the concept of an information "goodness factor" (interpreted on a 0–1 scale), which uses mathematical formalization to quantitatively assess proximity to reality [1]. The "goodness factor" is a term used in engineering to evaluate the efficiency and performance of devices, particularly electric motors and heat exchangers, by comparing their magnetic / electric properties or thermal/friction trade–offs, respectively. For motors, it helps design more efficient magnetic circuits, while for heat exchangers, it compares heat transfer (j factor) against pressure drop (f factor), with higher values indicating better performance for a given size.

However, the application of this factor remains limited when statistical methods (e.g., error margin calculation) are inapplicable due to irreproducible realities or interdependencies among corporate events.

This study aims to modernize information quality management by integrating artificial intelligence (AI) technologies. In corporate environments—particularly in procurement, production, and distribution—AI can provide effective support in the following areas:

- Autonomous Evaluation of Information Sources: AI–based systems can automatically analyse the reliability and relevance of data sources, filtering out biased or irrelevant information.
- Uncovering Correlations with Machine Learning: Machine learning models can identify hidden relationships between corporate performance and information quality, promoting more targeted data usage by decision–makers.
- Data Integration and Consistency: AI can harmonize heterogeneous data into structured formats, reducing contradictions and enhancing data transparency.

By applying these methods, human resource efficiency can improve, as decision–makers shift focus from data collection to meaningful interpretation. AI's objective analytical frameworks not only strengthen decision robustness but also contribute to long–term corporate stability.

THE NATURE OF REALITY AND ITS PERCEPTIBILITY IN LOGISTICS, WITH A FOCUS ON AI'S ROLE

Logistics is an interdisciplinary field where technical, natural, and social sciences play defining roles. In technical and natural sciences, we typically deal with an objective reality that can be understood and described through empirical tools—such as measurement and modelling. This allows for precise reproduction of reality and the development of predictive models. In contrast, social sciences—particularly economics—face limitations in fully reproducing reality, as human decisions, preferences, and behaviours are harder to formalize. Nevertheless, microeconomic models relevant to logistics (e.g., cost–benefit analysis) can approach objectivity through mathematical formalization.

Recent technological advancements, especially the emergence of AI, have opened new horizons in understanding reality. AI systems can analyse structured and unstructured data (e.g., text, images, videos), contributing to more accurate descriptions of complex systems. Advanced natural language processing (NLP) and computer vision enable AI to identify patterns and draw context–dependent inferences from large datasets, which are crucial for reliable predictive logic [5].

Furthermore, AI can simulate and predict the future behaviour of logistical systems through knowledge representation techniques. These systems not only describe real–world entities but also discover new insights through logical inference.

In summary, AI plays a significant role in enhancing the objectivity of logistical decision–making, similar to technical and economic models.

Spatiotemporal Perceptibility and AI's Role in Logistical Decision–Making

Logistical and production planning are heavily influenced by time and space. As highlighted in László Duma's doctoral thesis, corporate decisions often rely on uncertain demand forecasts [6]. This poses risks: products may not be manufactured, stored, or delivered in the right quantity, time, or composition. AI systems mitigate this uncertainty by analysing real–time demand and market trends, enabling more accurate production and inventory decisions.

M. Christopher emphasizes that reliance on demand forecasts is increasingly risky, leading to delayed decisions until more reliable data becomes available [7]. While this reduces error likelihood, it shortens procurement timelines. AI–driven dynamic forecasting allows decision–makers to respond faster and more accurately, alleviating time–related inefficiencies.

When demand predictability remains low, companies often resort to safety stocks or consignment inventories [8]. AI–based inventory optimization algorithms can adjust strategies dynamically based on consumption data, delivery times, and cost structures, reducing overstocking and shortages.

Can AI–processed and forecasted information ensure that decision–critical data becomes increasingly accurate, keeping deviations within tolerance levels?

Exploring the Internal Logic of Data Structures and AI's Role in Data–Driven Decision–Making

To enhance information's value as a resource, statistical and logical analyses are essential. Corporate decision–making is efficient only when data is treated as dynamic, continuously updated resources. AI plays a key role here: machine learning algorithms autonomously uncover data structures, correlations, and anomalies that would otherwise require significant human effort.

To form sound judgments, companies must contextualize events spatially and temporally. AI technologies, particularly time–series forecasting models, handle these relationships by simulating future events based on historical and current data, even accounting for multivariate nonlinearities.

Logical perception relies on comparison—using past or present data as references. However, binary "true/false" distinctions are insufficient for objective information. AI measures deviations and estimates their "goodness value," i.e., how reliable and relevant information is for decision–making.

If historical data predicts future consumption accurately, the information is correct and valuable. Otherwise, AI systems identify causes (e.g., data entry errors, non–representative samples, or market disruptions) and refine forecasts.

In uncertain scenarios, companies cannot afford models that fail under ambiguity. AI introduces adaptability: it learns, integrates diverse data sources (e.g., semantic web technologies), and provides decision–makers with timely, reliable information.

Overall, AI enhances not only data accuracy but also logical validation and corporate knowledge evolution.

We must recognize that the application of a binary logical scale of true (1) and false (0) is insufficient for interpreting and managing dynamic corporate environments. Companies operate in complex systems where preparing for future events is essential, and managing uncertainties is critical. A model that provides only exact, deterministic answers but cannot operate based on partial or probabilistic data cannot be considered viable in practice. AI systems offer significant advancements here, as they can manage uncertainty and refine predictive logic. Through their machine learning algorithms, AI can not only create probabilistic forecasts from historical data but also dynamically update them by incorporating new information and environmental changes. To reduce the gap between logically inferred expected values and actual future outcomes, continuous revision of forecasts and their supplementation with an adaptive 'goodness value'—which AI systems can refine and optimize in real time—is indispensable.

Rethinking logic: managing business uncertainty through the lens of artificial intelligence

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SPATIOTEMPORAL VARIABILITY OF INFORMATION QUALITY AND AI'S APPLICATIONS

Corporate data often lacks factual accuracy, as it is recorded by individuals with incomplete knowledge. In industrial settings, daily production planning relies on data whose accuracy directly impacts outcomes. While strategies like minimum inventory or constant production principles support aggregate planning, their success depends on input data precision.

AI offers real–time tracking of information quality, alerting decision–makers when data falls below desired thresholds. Continuous evaluation prevents flawed decisions and enables dynamic quality management.

Though production planning can be algorithmically managed, input reliability remains critical. AI dynamically calibrates forecasting models using incoming data, ensuring predictions evolve with market conditions. By re–evaluating past forecasts, AI increases information "goodness" over time.

Information quality is not static but a dynamically managed resource. Current systems often lack cross–temporal linkages between forecasts. AI bridges this gap through process mining, fostering organizational learning and decision–making resilience.

Ultimately, companies gain competitive advantages by consciously improving information quality and recalibrating models. AI is pivotal in managing uncertainty, refining predictive logic, and enhancing decision security.

BOUNDARY CONDITIONS AND REAL–TIME INFORMATION QUALITY ASSESSMENT WITH AI

Information reliability — expressed probabilistically ($p=1$ for objective truth, $p=0$ for no evidence) — varies spatiotemporally. For instance, order fulfilment probability (e.g., $p=0.1$) increases as information accumulates. AI tracks reliability in real time and flags insufficient data. Machine learning continuously re–evaluates inputs, improving model accuracy.

Modern logistics systems depend on forecast precision, yet regular reviews are rare. AI automates forecast–actual comparisons, identifies error sources, and suggests improvements via process mining.

In uncertain environments, companies must prepare for worst–case scenarios. AI employs robust optimization techniques to generate acceptable outcomes even with low information quality, simulating decision scenarios and predicting impacts.

Corporate information systems must evolve dynamically, with data value increasing over time. AI automates this process by learning source reliability, weighting decision inputs, and delivering increasingly precise recommendations. This enables companies to respond flexibly and robustly to rapid changes.

INTERPRETING CORPORATE INFORMATION QUALITY AND AI'S ROLE

Decision quality depends on two factors: necessity (how indispensable data is) and factuality (objective linkage to reality). AI prioritizes mission–critical data using machine learning.

Factuality measures objective verification of data. Fuzzy logic–based AI handles uncertainty, improving decision robustness in partial or incomplete information scenarios.

Information quality (VIgdn) is calculated as:

$$VIgdn = Ir \times Ic,$$

where
- ≡ Ir = necessity and
- ≡ Ic = factuality.

Wang and Strong (1996) define information quality across four dimensions: accuracy, completeness, timeliness, and consistency [9]. AI automates their assessment and adapts to corporate changes.

AI also addresses information gaps by simulating impacts and recommending compensatory strategies, crucial in crises or volatile environments.

CONCLUSION

Ensuring corporate information quality is complex, constrained by reality's limitations and information management challenges. AI holds significant potential to enhance data quality, decision efficiency, risk management, and process optimization.

As Shollo and Galliers (2016) note, business intelligence systems contribute not only operational insights but also organizational knowledge, elevating decisions' strategic value.

Investing in AI–driven information systems will be critical for companies to remain competitive in dynamic economic landscapes.

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