Integrating Deep Learning: Humans and Machines Managing Financial Risk in Oil & Gas Industry

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Abstract. *Financial decision-making in large industries is increasingly complex due to market volatility and high capital exposure, requiring intelligent tools for strategic planning. This study proposes a Deep Learning framework integrated with Human-Computer Interaction (HCI) techniques to forecast oil prices and mitigate financial risk. Four models were evaluated with hyperparameter optimization on real-world datasets. A key contribution is the incorporation of graphical result visualization, enhancing user interpretation and decision-making. The findings underscore the value of AI-driven analytics and interactive interfaces in developing transparent financial decision support systems.*

1. Introduction

The continuous advancement of digital technologies has profoundly reshaped financial decision-making processes in critical industrial sectors such as oil and gas. As data-driven strategies become fundamental to risk assessment, human-computer interaction (HCI) has become an essential bridge between financial analysts and intelligent decision-support systems. The exponential growth of financial and operational data necessitates interfaces that effectively integrate artificial intelligence (AI), ensuring that complex models remain interpretable and accessible for high-stakes decision-making [Yang 2022].

Deep Learning models have changed predictive analytics within financial environments by capturing nonlinear relationships, seasonal trends, and exogenous shocks in economic time series. These capabilities significantly improve risk analysis in large-scale industrial projects [Song 2022]. In the oil and gas sector, where high investment volumes and exposure to geopolitical uncertainty demand precision, leveraging AI-driven forecasting models enhances the reliability of strategic planning and financial risk mitigation.

The intersection of Deep Learning, HCI, and financial risk management remains an emerging field, but with promising advances. Recent research highlights the role of intelligent HCI in reducing users' cognitive load and increasing trust in automated systems through explainability and adaptive interaction [Lv et al. 2022]. In highly complex environments like offshore oil exploration, models must be accurate, interpretable, and embedded in interfaces that allow continuous user-system interaction.

Beyond enhancing analytical precision, AI-driven systems can address cognitive biases that influence financial decision-making. Research such as [Hasan et al. 2022] demonstrates that AI reduces judgment errors stemming from emotional influences or unconscious heuristics, a factor that is particularly relevant in capital-intensive industries. Reinforcement learning and recurrent neural networks have shown promise in forecasting critical financial variables and enabling adaptive risk control strategies.

Furthermore, integrating AI with high-performance computing and simulation platforms has expanded the capabilities of intelligent financial systems to manage high-dimensional data amid volatile market conditions [Atadoga et al. 2024], [Jia et al. 2022]. These advanced computational frameworks facilitate robust asset pricing, precise cash flow forecasting, and reliable Value-at-Risk (VaR) estimation, making them indispensable in capital-intensive projects.

This research aims to evaluate the use of the GluonTS library in forecasting time series relevant to the Oil and Gas sector, particularly for subsea systems in ultra-deepwater environments like the Brazilian Pre-Salt.

The key contribution of this research is developing a Deep Learning framework that, when combined with HCI strategies, provides an effective tool for decision-makers in complex financial environments, particularly within the oil and gas sector. This approach enables informed financial strategies while ensuring seamless human interpretation of AI-driven insights by offering high-precision predictive capabilities alongside intuitive and interactive visualizations. The subsequent sections further explore this integrated approach's foundations, methodologies, and empirical findings, reinforcing its relevance in financial decision support systems.

2. Human-Computer Interaction (HCI) and AI applications

Human-Computer Interaction research has advanced significantly with AI integration, moving towards developing more adaptive, intuitive, and user-centered systems. This new approach seeks to improve usability and efficiency and promote a more collaborative and natural interaction between humans and machines. Technologies such as Deep Learning, affective computing, and interactive learning have enabled systems that better understand the user's context, emotions, and intentions, enabling personalized and adaptive responses. This direction is particularly relevant in the current scenario of AI expansion in critical areas, such as health, education, and agriculture, where effective interaction between humans and intelligent systems is essential to maximize technological benefits while minimizing risks and adoption barriers.

By integrating AI into HCI, research not only expands the possibilities for innovation but also reinforces the relevance of Human-Computer Interaction as an essential interdisciplinary field for the future of technology. Researchers explore fundamental aspects such as listening, speaking, reading, writing, and other senses, enabling more natural interactions between humans and systems. The literature highlights key challenges, such as affective computing, which provides significant insights into current and future applications, expanding the horizons of innovation in these fields. [Ren and Bao 2020]

Various studies in HCI focus on addressing complex challenges through innovative solutions. For instance, the development of the online tool Abstrackr exemplifies advancements that facilitate citation screening in systematic medical reviews by leveraging Machine Learning to reduce manual effort in reviewing vast amounts of literature [Wallace et al. 2012]. Similarly, in neural machine translation (NMT), systems have been designed to adapt in real time during post-editing or interactive translation phases. These systems utilize human corrections to incrementally update translation models incrementally, enhancing both efficiency and accuracy [Peris and Casacuberta 2019].

Another significant area within HCI involves image processing, such as a novel method for efficiently segmenting histopathological images using interactive Human-Computer learning. This approach seeks to minimize the reliance on labor-intensive manual annotations by integrating self-supervised contrastive learning with tissue prototype learning, enabling more accurate and efficient segmentation [Pan et al. 2023]. Moreover, advancements in agricultural AI highlight the potential of Human-Computer collaboration. By combining farmers' expertise with AI's computational power, researchers promote interactive Human-Computer learning to enhance decision-making processes and alleviate the workload, paving the way for more sustainable and efficient farming practices [Backman et al. 2023].

Just as the Oil and Gas sector utilizes complex time series, such as oil prices, to guide future financial investment decisions, the focus of this research, the literature on HCI, also presents relevant studies applied to time series. One notable example is the application of Machine Learning (ML) in systems designed for intermediate users working with sensory data, such as heart rate monitors. Among these initiatives is Gimlets, a graphical and interactive tool developed to support the entire Machine Learning pipeline, covering preprocessing, feature extraction, model building, and results visualization. The system aims to democratize the use of ML to handle large, multisensory, and highly complex datasets, enabling intermediate users to develop previously considered unfeasible models due to technical challenges [Kim et al. 2017].

Computational modeling is inherently interdisciplinary, requiring integrating knowledge from multiple domains at different stages [Skiba et al. 2022], [Helmy et al. 2010]. In this paper, we present a case study illustrating this multidisciplinary process. The first stage, problem formulation, relies on specialized knowledge of finance as applied to the O&G sector.

Mathematical expertise is central in the subsequent modeling phase, underscoring the importance of human proficiency in finance and mathematics. During the simulation and software development stage, deep knowledge of Computer Science is critical, marking the transition to a collaborative effort between human intelligence and machine processing power.

Figure 1 illustrates the distinctions among these modeling scenarios and highlights the evolution from purely mathematical modeling to human-centered Deep Learning applications. While classical models rely heavily on human formulation and static interpretation, Deep Learning systems enable dynamic simulation and predictive capacity at scale. This collaboration relies on sophisticated algorithms running at high speed, requiring substantial computational resources. However, the most impactful comes when these predictions are combined with visual results that support intuitive interpretation. Graphical representations of Deep Learning results enhance the transparency of algorithmic reasoning and empower decision-makers to act with confidence and speed. In complex financial environments, such as those involving volatile commodity markets like oil, this synergy between computational power and human-centered visualization becomes critical to generating robust, actionable insights.

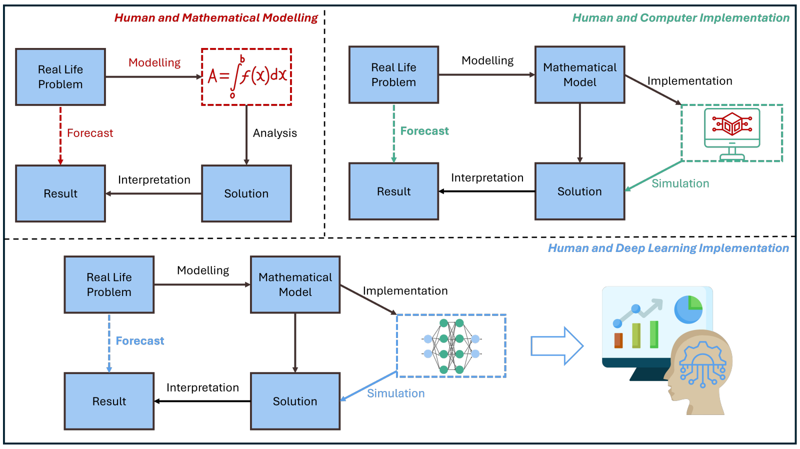

Figure 1. Comparison of problem-solving processes using traditional mathematical models vs computational approaches and AI methods.

A relevant study in HCI, utilizing time series data from pediatric trauma cases, introduces a framework for a learning-based method for pattern discovery and prediction in high-dimensional, multimodal, and correlated data. The proposed model offers an interactive and incremental system that enables users to adjust based on new data or manual corrections without requiring complete model retraining. This approach facilitates continuous adaptation to changes and fosters effective Human-Computer Interaction in the learning process [Guo and Hofmann 2017].

3. The framework

Monitoring global oil price fluctuations is critical for significant oil and gas players. Accurate projections of future oil prices serve as a cornerstone for strategic decision-making in the sector. These forecasts enable suppliers to plan budgets effectively, optimize financial resources, and mitigate risks. As illustrated in Figure 2, the high volatility of the oil market underscores the relevance of the case study presented in this paper.

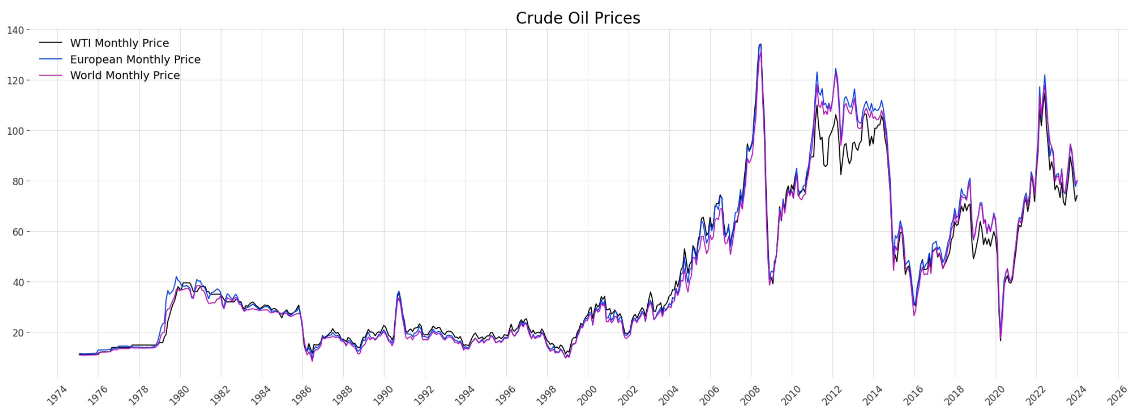

Figure 2. Historical oil price dynamics.

In the Brazilian Oil & Gas Exploration and Production sector, contracts for developing submarine oil extraction systems typically occur through tender processes. In this context, the period from proposal submission to contract formalization with the winning bidder averages around six months. Furthermore, when factoring in contracting timelines and the lead time for procuring steel, the primary raw material, a production planning margin of approximately 12 months becomes essential to mitigate potential disruptions.

This study introduces a robust framework for forecasting oil prices, designed to support decision-making in large-scale projects by mitigating financial risk. The proposed framework integrates Deep Learning libraries, enabling the application of complex models with minimal coding complexity. This approach encourages broader adoption in support sectors such as finance by reducing technical barriers and leveraging HCI techniques to enhance usability and accessibility.

Furthermore, the framework presented in Figure 3 emphasizes a data-driven methodology, facilitating the execution of sophisticated predictive models without requiring extensive programming expertise. This accessibility is particularly valuable in industries seeking reliable forecasting tools for risk management. By streamlining complex modeling processes, the framework empowers professionals in financial decision-making, promoting informed strategies in high-stakes economic environments.

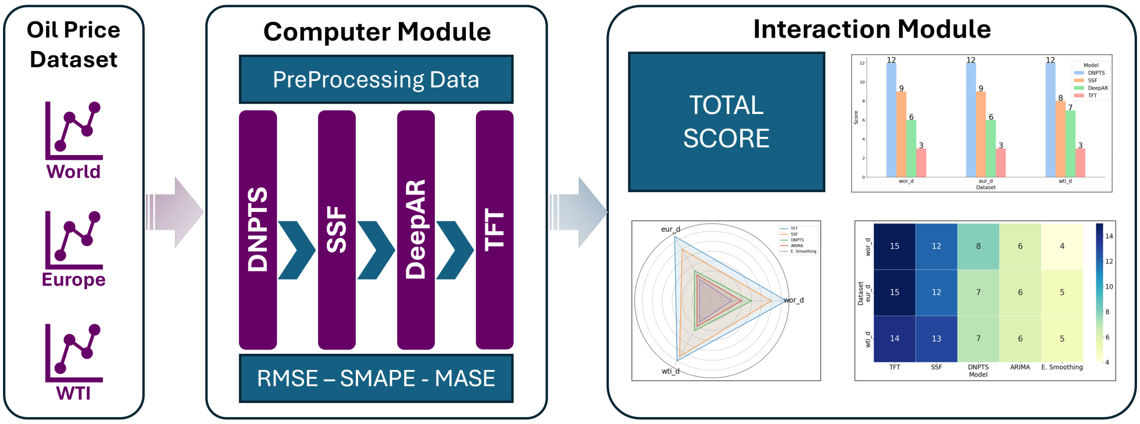

Figure 3. Framework using Deep Learning Library focused on HCI.

We employed the GluonTS library with Optuna for hyperparameter optimization. We applied it to time series data of Brent oil prices and Brazilian/imported steel prices, which are essential in subsea product manufacturing for oil and gas exploration. The project optimizes model selection to identify the best technique for each dataset, aiming to construct a financial risk index based on steel price volatility. A key challenge in Brazilian Oil & Gas projects is the discrepancy between raw material procurement prices, determined months before contract signing, and the final contract value, which often fails to reflect market fluctuations.

Recent research using Deep Learning models, such as Convolutional Neural Networks (CNN) [Mohsin and Jamaani 2023], Temporal Fusion Transformer (TFT) [He et al. 2023], and Recurrent Neural Networks (RNN) using LSTM and GRU [Sen and Dutta Choudhury 2024], [Wang et al. 2023], have datasets with daily closing values of the oil market in China and the United States. Although published between 2023 and 2024, the datasets are from periods up to 2020 - 2021, which may offer distortions with applications carried out between 2022 and 2024, a post-pandemic period with a cooling in the barrel price.

For the projection of oil prices, four models implemented in PyTorch from the GluonTS library were used: DeepAR, TFT, Simple Feed Forward (SFF), and DeepNPTS (DNPTS). All are aimed at time series with univariate data.

The DeepAR model is a time series forecasting technique based on recurrent neural networks (RNNs), specifically architectures of Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU). This model is designed to handle multiple time series simultaneously, leveraging cross-information between them to improve the accuracy of predictions.

The Temporal Fusion Transformer model combines the transformer's ability to capture long-range dependencies in the data with a specific architecture to fuse two different architectures: self-attention with Long Short-Term Memory. The TFT also efficiently handles multiple data sources, integrating information from past time series, static attributes that do not change over time, and exogenous variables that may affect the predictions.

The Simple Feed Forward (SFF) model is a neural network for time series forecasting. The SFF model, as the name suggests, is a simple feedforward neural network structure, meaning that the connections between the nodes do not form cycles. This model comprises several layers, where each layer receives input from the previous layer, processes this input, and passes the output to the next layer.

Finally, the DeepNPTS model does not assume a specific parametric form for the series. Instead, it utilizes data-based methods to identify patterns, trends, and seasonality without imposing a pre-defined structure like parametric models (ARIMA, SARIMA). It represents an innovative approach to time series forecasting, integrating the flexibility of non-parametric methods with the Deep Learning capability of neural networks.

4. Empirical Experiment and Analysis

The experiment applied four Deep Learning models from the library with PyTorch integration: Simple Feed Forward, DeepAR, Temporal Fusion Transformer, and DeepNPTS. The experiments were conducted in a dedicated virtual environment using Python 3.12.0 and Visual Studio Code on Windows 11. All models were run on a PC with 64 GB RAM, NVIDIA GeForce RTX 4070 Ti Super GPU, and Intel Core i7-10700K CPU.

The global Oil and Gas sector is characterized by three price benchmarks that serve as global references for oil pricing: the American market with West Texas Intermediate (WTI), Brent oil for the European market, and the global average price set by the Organization of the Petroleum Exporting Countries (OPEC). Each series is derived from real-world data based on the price per barrel in U.S. dollars. The daily price series begins on January 4, 2016, and ends on February 16, 2024. The last 300 records were employed in the daily series for the model's testing phase. All the time series were extracted from the Federal Reserve Bank of St. Louis. All datasets underwent an individual preprocessing phase, accounting for observed seasonality and trends and analyzing missing data or additional irregularities.

Data preprocessing included log differencing with a 12-month moving average, which improved results. Hyperparameters were optimized using Optuna over 30 iterations per model. After training and testing, each model was ranked based on RMSE, SMAPE, and MASE, with a total score summarizing overall performance.

The accuracy of each model is measured using seven statistical indices calculated by the library itself: Root Mean Square Error (RMSE), Symmetric Mean Absolute Percentage Error (SMAPE), and Mean Absolute Scaled Error (MASE). Additionally, we have developed a classification approach that considers the combination of all these metrics through a score, allowing us to determine the best model among all those tested automatically. This automation in the developed model brings more clarity to the interpretation of results, offering a more concise structure to assist decision-makers based on the obtained outcomes. A model that demonstrates high levels of accuracy in predicting oil prices helps mitigate the imminent risk of financial loss in oil and gas sector projects.

Table 1 shows consistent results across the three datasets. The final scores help decision-makers automatically identify the best-performing model for forecasting daily oil prices, without requiring manual analysis.

Table 1. Results of Daily Oil Barrel Price

Model	**RMSE**		**SMAPE**		**MASE**		**Total**
	Result	Scr	Result	Scr	Result	Scr	Score
World Daily Price							
DNPTS	0.039	4	1.552	4	1.622	4	12
SFF	0.041	3	2.427	3	1.689	3	9
DeepAR	0.044	2	2.582	2	1.826	2	6
TFT	0.083	1	5.785	1	3.356	1	3
Europe Daily Price							
DNPTS	0.0371	4	1.841	4	1.588	4	12
SFF	0.043	3	3.290	3	1.903	3	9
DeepAR	0.044	2	3.551	2	1.961	2	6
TFT	0.107	1	8.848	1	4.257	1	3
WTI Daily Price							
DNPTS	0.036	4	1.570	4	1.843	4	12
SFF	0.0376	3	2.238	2	1.881	3	8
DeepAR	0.039	2	2.097	3	1.980	2	7
TFT	0.045	1	2.627	1	2.284	1	3

The DNPTS model consistently outperforms all others worldwide, Europe, and WTI Daily Price datasets, achieving perfect total scores (12). Its low RMSE, SMAPE, and MASE values confirm its superior accuracy and robustness, especially under volatile market conditions. SFF ranks second across all datasets, with solid results but slightly higher error rates than DNPTS. DeepAR performs moderately, with consistent but less precise predictions, while TFT ranks last due to its high SMAPE and MASE values, indicating lower reliability.

DNPTS's architecture, tailored to model nonlinear dependencies and temporal patterns, proves highly effective for forecasting oil prices. Its resilience to data noise, particularly evident in the SMAPE metric, is crucial in contexts influenced by sudden geopolitical or economic shifts. These strengths make DNPTS the most adaptable and accurate model among those tested.

The development process incorporated Deep Learning techniques and hyperparameter tuning using Optuna, generating approximately 130,000 parameters per model across 30 scenarios. Such complexity would be unfeasible through human analysis alone. This highlights the value of human-AI collaboration, where artificial intelligence enhances the capacity for critical decision-making without replacing human judgment, strengthening trust in AI-driven tools for strategic applications in energy markets.

The empirical stage of this research highlights the value of visual representation in financial decision-making, particularly in high-risk sectors like Oil and Gas. Deep Learning interpretability becomes a strategic asset, enabling decision-makers to assess models and anticipate financial impacts through comparative visualizations. This process exemplifies HCI's role in reducing cognitive load and enhancing confidence in AI-driven analytics, reinforcing the applicability of predictive models in volatile markets.

5. Analysis and Insights

All computational models selected for this research are based on simple mathematical models. However, given the nature of the study object, the volume of data applied, the number of iterations, and the activity of fine-tuning the hyperparameters, it becomes impractical for a human to perform the calculations manually. Nonetheless, the tools and types of models chosen are based on decisions made by human intelligence, necessitating this Human-Computer Interaction.

Without this collaborative effort, finding the best solutions to support the decision-maker is impossible. The generation of probable scenarios regarding the projection of oil prices based on thousands of possible parameters is inherent to machines with prior human configuration.

The models, tools, libraries, and equipment are decisions that can directly impact the quality of the results. These decisions are not based on assumptions inspired by common knowledge but on prior scientific studies. These AI techniques, including Deep Learning, can lead to different and increasingly effective data treatments by improving the developed models, which would not be possible without human knowledge and intelligence intervention. The level of success of the studies developed will depend on the human effort put into the studies and the machines.

With this type of presentation, the decision-maker will be able to choose the best model quickly, as it is visually possible to identify the best option and the most assertive way, since the entire structure of the computational modeling has been created and defined by professionals who understand both technology and the business in which the company operates.

The high volatility of oil prices, a key commodity that directly influences investment strategies in the Oil and Gas sector, demands robust tools beyond traditional numerical reporting. Recent studies show that interactive visual analytics systems support decision-makers when interpreting model outputs under volatile conditions [Niu et al. 2021]. For instance, visualization frameworks designed for systemic financial networks have demonstrated the benefits of simulation-intervention-evaluation loops, allowing users to identify the optimal mitigation strategy under risk propagation scenarios.

This logic can be extended to the Oil and Gas domain, where the forecasting of barrel prices impacts procurement cycles, contract formulation, and raw material investment decisions. Thus, implementing visual exploration tools that contextualize predictive outputs, such as SMAPE or VaR variations, can transform raw forecasts into strategic insights for business users operating in complex environments.

Although the experimental results are presented in tables, it's possible to make the visualization quicker for the decision-maker, as shown in Figure 4. The same results from the previous section's tables can be viewed with only the information relevant to the user, indicating the best model for each dataset.

The presented charts show that the DNPTS model consistently outperforms the others across the three simulated oil price datasets (wor_d, eur_d, and wti_d), followed by SFF, DeepAR, and TFT. This consistency is reinforced by the bar chart and the radar chart, highlighting DNPTS's robustness across different scenarios. The heatmap confirms this pattern, enabling a quick visual comparison of results and emphasizing model performance differences. From a decision-making perspective, these results suggest that, for oil price forecasting applications, especially in highly volatile environments, prioritizing DNPTS may yield gains in accuracy and reliability. Furthermore, the simultaneous visual analysis allows the identification of the best overall model and specific model–dataset combinations that could be leveraged to optimize hedging strategies, pricing, and financial risk mitigation.

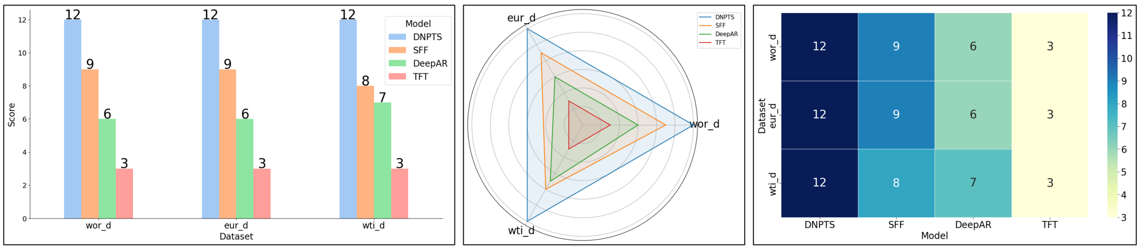

Figure 4. Result in different views.

Furthermore, visual analytics systems tailored to the Oil and Gas industry, like the Oil and Gas Visual Exploration System (OGVES), illustrate how web-based interfaces can democratize access to complex production and market data, improving operational response and collaboration among stakeholders [Li et al. 2017]. Combined with advances in Machine Learning explainability, recent work also suggests that visualization supports the interpretation of model behavior and enhances trust in algorithmic predictions, particularly in high-stakes environments [Ganguly et al. 2024].

These findings align with the case presented in this research, where combining Deep Learning models and interactive visual feedback helps identify the most reliable forecasting method. By simplifying the communication of results and reducing cognitive overload, graphical outputs serve as an essential interface between computational models and human judgment, reinforcing the importance of HCI in financial decision-making within volatile commodity markets.

6. Conclusion

Companies are leading a wave of transformations driven by technological progress, highlighting the significant influence of AI. This advancement is breaking traditional paradigms, opening doors to new opportunities, and rebuilding the nature of work. Several studies available in the scientific literature indicate that these radical changes tend to preserve jobs rather than eliminate them, contradicting the common fear that automation and AI will result in massive unemployment [Zierahn et al. 2016].

The increasing adoption of automation, artificial intelligence, and advanced technologies has replaced various repetitive and manual tasks, significantly impacting low- and high-skilled jobs. Continuous learning and adaptability are essential skills, reflecting a growing demand for creative, social, and technical competencies over physical or routine abilities. This scenario highlights the need to rethink professional training and qualification models to meet the constantly evolving labor market demands [Schwab 2016].

Unlike machines, humans excel in complex and innovative tasks, reinforcing the need for technology to foster collaboration between human labor and capital. Interactive technologies create new roles, countering full automation and driving the coevolution of human skills with AI [Acemoglu and Restrepo 2018]. In this context, Human-Computer Interaction (HCI) ensures that AI promotes inclusion and societal balance rather than deepening inequalities.

Moreover, HCI reduces social and organizational disparities by promoting inclusive access to intelligent tools. It mitigates bias originating from human-driven data collection [Calleo and Rosato 2023] and supports the adoption of AI in financial sectors such as Treasury and Planning, where critical decisions require clarity, trust, and contextual relevance.

A significant challenge in large organizations is ensuring information security when using AI. Integrating scientific knowledge into corporate routines can be an effective strategy for adopting internally developed solutions, allowing researchers and financial teams to work collaboratively. This approach enhances confidence in AI-driven applications and improves financial forecasting, adding shareholder value.

This study demonstrated the potential of Deep Learning models integrated with HCI techniques to support complex decision-making in the oil and gas industry. To validate this framework, future research should focus on empirical tests with industry professionals in real-world operational settings, assessing usability, accuracy, and strategic impact. Refining user interaction techniques and evaluating cognitive load will enhance model transparency and adaptability, ensuring predictive analytics align with industry-specific challenges. This approach lays the foundation for advancing financial intelligence and risk assessment in high-stakes environments by bridging Deep Learning methodologies with user-centered design principles.

Thus, the synergy between AI models and human expertise remains crucial to delivering sustainable and strategic value to organizations operating in volatile markets. The successful adoption of AI-driven financial decision support systems will depend on blending technological precision with practical usability, enabling informed, data-driven strategies in the global oil and gas sector.

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