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Evaluation of the Performance of Deep Learning Models in Cryptocurrency Price Prediction: A Case Study of Bitcoin, Dogecoin, Ethereum, and Ripple

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ABSTRACT

Cryptocurrencies, as one of the emerging asset classes, have gained significant popularity in recent years. Accurate forecasting of cryptocurrencies' prices has become highly attractive for both researchers and investors due to their volatile and non-linear price behavior. However, predicting the cryptocurrencies' prices accurately remains challenging due to their substantial fluctuations and complex dynamics. Research findings indicated that the methods of deep learning and neural networks outperform traditional econometric approaches in forecasting financial and economic time series. Among the techniques of neural network and deep learning, various types of Recurrent Neural Network (RNN) models have been proven to be effective. This study employed three Recurrent Neural Network architectures—RNN, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—to predict the logarithm of the prices of four major cryptocurrencies of Bitcoin (BTC), Dogecoin (DOGE), Ethereum (ETH), and Ripple (XRP). Daily time-series data from January 17, 2018, to December 18, 2024, were utilized for this purpose. The data were collected using the cryptocmd python package. The experimental results which were assessed using four metrics—Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (SMAPE)—revealed two key findings: First, as the forecasting horizon increases, the required input size for achieving the best predictions increases for all models. Second, the LSTM model demonstrates a superior performance in predicting the prices of major cryptocurrencies for 1-day and 30-day horizons, whereas the GRU model exhibits the lowest prediction error for a 7-day horizon. These findings provided valuable insights for estimating the mean equation, which is instrumental in forecasting the expected returns of cryptocurrency assets for risk management purposes.

KEYWORDS

Artificial Intelligence, Cryptocurrencies, Deep Learning, Gated Recurrent Units, Long Short-Term Memory, Recurrent Neural Networks.

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Introduction

Cryptocurrencies are digital assets that have gained significant attention in recent years. By nature, they are decentralized, meaning their issuance and value are not controlled by any central authority or institution. Consequently, their prices are highly volatile, making the prediction of future prices a challenging and complex task. Accurate forecasting of cryptocurrencies' price is crucial for informed decision-making and reducing the risks associated with these assets for investors, traders, and financial analysts (Kubat, 2015). Various methods exist for predicting the cryptocurrencies' prices, including time-series analysis, sentiment analysis, and neural networks and deep learning algorithms. However, due to the dynamic and complex nature of cryptocurrencies, these methods face limitations in terms of their predictive accuracy.

Time series forecasting plays a pivotal role in the cryptocurrency market, where accurate predictions of asset prices and volatility can significantly influence investment strategies, risk mitigation, and liquidity management. Traditional statistical and econometric models, such as ARIMA and GARCH, have historically been employed for financial forecasting. However, their reliance on assumptions like linearity, stationarity, and normality—rarely satisfied in cryptocurrency markets—limits their effectiveness. Cryptocurrencies exhibit extreme volatility, non-linear price dynamics, and susceptibility to exogenous shocks rendering conventional methods inadequate.

In recent years, machine learning—particularly deep learning architectures—has emerged as a transformative tool for cryptocurrency forecasting. Advanced neural network techniques, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have gained significant traction due to their ability to capture complex temporal dependencies, abrupt trend reversals, and multi-scale patterns inherent in crypto data. These models, as part of the broader family of Artificial Neural Networks (ANNs), dynamically adapt to market anomalies like pump-and-dump cycles or flash crashes. By overcoming the limitations of traditional statistical methods, deep learning enables robust predictions across diverse horizons—from short-term intraday fluctuations to long-term trend analysis—positioning it as a cornerstone of modern cryptocurrency analytics. This growing trend is supported by extensive international research demonstrating the efficacy of LSTM and GRU in modeling long-term dependencies and nonlinear relationships, particularly in volatile asset markets like cryptocurrencies.

Despite extensive international research employing various neural networks and deep learning models to predict economic variables, there is a scarcity of published studies in this domain in an Iranian context. Moreover, apart from the prediction of Bitcoin price in the study by Sayadi Nezhad et al. (2023), the prediction of other major cryptocurrencies has not been addressed in prior Iranian research studies. In light of the aforementioned considerations, the primary objective of this paper is to predict the logarithm of the prices of four major cryptocurrencies using three models—RNN, LSTM, and GRU—and to identify the superior model with the lowest prediction error, utilizing daily price data from January 17, 2018, to December 18, 2024. This study is innovative in several respects: First, in addition to using the widely used RNN and LSTM methods, the GRU method is also employed. Second, the prices of four key cryptocurrencies are predicted, whereas previous studies have predominantly focused on Bitcoin. Third, approximately 15% of the last observations from the end of the period (around 360 observations) are reserved for testing the prediction accuracy, followed by the calculation of prediction errors for 1-day, 7-day, and 30-day horizons. In this paper, the data under examination were analyzed within the framework of univariate time series analysis, addressing the key limitations inherent in Recurrent Neural Network (RNN) family architectures. Additionally, lagged variables and other deterministic variables, such as days and months of the year, were also incorporated as explanatory variables in the analysis.

Literature Review

The prediction of financial time series primarily focuses on forecasting the asset prices (Tsay, 2005). Despite the existence of various methodologies, recent research has concentrated on using deep learning models to predict future movements in the assets (Fischer & Krauss, 2018). This encompasses a wide range of topics, including stock price prediction, index forecasting, foreign exchange rates, commodity prices (e.g., oil and gold), bond prices, and cryptocurrency prices (Sezer et al., 2020).

The value of cryptocurrencies theoretically reflects their desirability as a medium of exchange, which has significantly increased over the past decade. Given the growing importance of cryptocurrencies for financial systems, early studies focused on their volatility, confirming that these fluctuations are substantial (Klein et al., 2018) and extremely challenging to predict (Fang et al., 2020; Walther et al., 2019). Furthermore, some empirical studies have highlighted several key characteristics, such as the "fat-tailed distribution of cryptocurrency returns", the "weakening of absolute and relative autocorrelation of returns at different rates", the "strong presence of leverage effects and volatility clustering", "long-term dependencies in volatility and returns", and "compliance with power-law dynamics in prices and volatility" (Zhang et al., 2018). These features make cryptocurrency price prediction difficult and investing in them riskier than traditional financial assets. Additionally, empirical findings indicate that Bitcoin and other cryptocurrencies exhibit cyclical patterns in recent years (Dong et al., 2022; Kyriazis et al., 2020).

Most studies on cryptocurrency price prediction have relied on traditional statistical methods. For instance, Catania et al. (2019) utilized a vector autoregression model to forecast Bitcoin, Ripple, Litecoin, and Ethereum prices, while Conrad et al. (2018) employed the GARCH-MIDAS model to study the impact of mid- and long-term S&P 500 volatility on Bitcoin. Similarly, Walther et al. (2019) used the GARCH-MIDAS model to predict volatility for five major cryptocurrencies.

In recent years, researchers' attention has shifted toward deep learning models for cryptocurrency price prediction. A notable contribution in this area is the work of

Kristjanpoller and Minutolo (2018), who introduced the MLP-GARCH model for predicting the volatility of Bitcoin price. Artificial neural networks represent a collection of advanced techniques and computational methods in neural networks and deep learning. These networks consist of structures made up of interconnected simple processing units capable of performing highly parallel computations to process data efficiently (Goodfellow et al., 2016). Nakano et al. (2018) also applied Multi-Layer Perceptron (MLP) models to predict Bitcoin returns. Empirical evidence suggests that this approach outperforms ARIMA, Prophet, and Random Forest models in forecasting directional movements (Ibrahim et al., 2021).

Artificial neural networks offer numerous advantages over other methods, such as their ability to use nonlinear functions, perform parallel computations, learn from data, and incorporate qualitative information. Using nonlinear functions improves the evaluation of input data and reduces the time required for assessment due to their parallel computation capabilities (Limsombunchai et al., 2004).

Recently, recurrent neural networks (RNNs) like LSTM and GRU have been employed to automatically extract short-term patterns from high-frequency cryptocurrency time series. Notable examples include studies by Patel et al. (2020) and Parekh et al. (2022), both of which utilized LSTM and GRU models. These advanced deep learning-based neural networks have effectively learned complex sequential patterns in data, explaining why LSTM has outperformed the traditional neural network models like MLP in recent studies (Chen et al., 2021; Lahmiri & Bekiros, 2019; Li & Dai, 2020). Moreover, according to Zhang et al. (2021), the GRU model demonstrated a superior predictive performance for four major cryptocurrencies compared to both traditional neural network methods and LSTM-based models. Seabe, et al. (2023) used LSTM, GRU, and Bi-Directional LSTM for forecasting the cryptocurrency prices. Hamayel et al. (2021) used GRU, LSTM and bi-LSTM machine learning algorithms for predicting the cryptocurrency prices.

Methodology

Research Method

1. Simple Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) have been one of the cornerstones of deep learning research for several decades. The concept of RNN was first introduced in the 1980s by David Rumelhart, Geoffrey Hinton, and Ronald Williams, who proposed the use of recurrent connections to model temporal relationships in data. The RNN models are suitable for multivariate time-series data and are capable of capturing temporal dependencies across different time periods (Che et al., 2018; Graves, 2012). In an RNN, input values enter the network, and output values are generated based on these inputs and network parameters.

The backpropagation algorithm can be applied to train a recurrent network by unfolding it over time and constraining certain connections to maintain consistent weights across all time steps (Xu et al., 2018). Thus, RNNs can encode previous information into the current hidden layer during the learning process, enabling effective learning of time-series data (Bengio et al., 1994).

In simple recurrent neural networks (RNNs), the output y_t is calculated as follows:

$$y_t = f(W_y h_t) \tag{1}$$
$$h_t = \sigma(W_h h_{t-1} + W_x x_t) \tag{2}$$

Here, W_y, W_h, and W_x represent matrices for the hidden layer output h_t, the activity of the previous hidden layer h_{t-1}, and the input x_t, respectively. The recurrence in Equation (2) links the current hidden layer activity h_t with the previous hidden layer activity h_{t-1}. This dependency is nonlinear due to using sigmoid function $\sigma(.)$ (Yao et al., 2015).

2. Long Short-Term Memory (LSTM)

Theoretically, RNNs should possess the ability to learn sequences of any complexity. However, empirical observations indicate that these networks struggle to retain relevant information from past inputs over long durations. This inability to store and preserve past information leads to instability when generating sequences (Hansson & Rostami, 2019). Addressing this instability requires longer-term memory capabilities, as a network with extended memory can still learn from inputs despite long intervals between significant events. This need led to the introduction of the Long Short-Term Memory (LSTM) model, a subtype of RNN with enhanced storage and access capabilities compared to traditional versions. Consequently, LSTMs can detect important features in input sequences early on and propagate them along a long path while maintaining long-term dependencies throughout the process (Chen et al., 2017).

Hochreiter and Schmidhuber (1997) were the first researchers who introduced the LSTM model, which was later refined in Graves' research study (2012). Designed as a primary alternative to RNNs, LSTMs address issues such as vanishing gradients and facilitating more efficient computations. In many recent studies, LSTMs have demonstrated a superior performance and are relatively easier to train. As a result, LSTMs have become baseline architectures for processing sequential data with temporal information (Jozefowicz et al., 2015).

An LSTM unit consists of a cell and three gates: the input gate, forget gate, and output gate (Cho et al., 2014). The cell serves as the memory component of the LSTM, used to store values over arbitrary time intervals. In LSTMs, a linear dependency is introduced between the memory cells c_t and their previous statec_{t-1}. Additionally, LSTMs include input and output gates, which apply nonlinear functions to the input and output of the LSTM, respectively. The relationships within an LSTM are expressed as follows:

$$i_t = \sigma(W_{xi} x_t + W_{hi} h_{t-1} + W_{ci} c_{t-1}) \tag{3}$$
$$f_t = \sigma(W_{xf} x_t + W_{hf} h_{t-1} + W_{cf} c_{t-1}) \tag{4}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot tanh(W_{xc} x_t + W_{hc} h_{t-1}) \tag{5}$$
$$o_t = \sigma(W_{xo} x_t + W_{ho} h_{t-1} + W_{co} c_t) \tag{6}$$
$$h_t = o_t \odot tanh(c_t) \tag{7}$$

Herei_t, f_t, and o_t represent the input gate, forget gate, and output gate, respectively (Yao et al., 2015).

3. Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU), introduced by Cho et al. (2014), shares many similarities with LSTM but differs in how the gates are applied. Unlike LSTM, which uses three gates, GRU employs only two gates: reset gate and update gate. The reset gate determines how to combine new input with previous memory and controls the degree to which the prior memory is ignored. Smaller values for the reset gate indicate that the previous memory is largely disregarded. The update gate specifies the extent to which the prior memory is retained (Song, 2018). A key distinction between GRU and LSTM is that GRU does not have a separate memory cell; instead, its operations are simplified as follows:

$$h_t = (1 - z_t)h_{t-1} + z_t\tilde{h}_t \tag{8}$$
$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \tag{9}$$
$$\tilde{h}_t = tanh(W_h x_t + U(r_t \odot h_{t-1})) \tag{10}$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \tag{11}$$

Here, h_t represents the output of the GRU at time t, while z_t and r_t denote the update and reset gates, respectively. W_z, W_h, W_r, U_z, and U_r are weight matrices within the GRU architecture (Yao et al., 2015). The GRU's streamlined structure reduces computational complexity while maintaining strong performance in capturing temporal dependencies.

Time-Series Cross-Validation

Time-series cross-validation is a method used to assess how well a model performs on historical data. Unlike standard cross-validation, which randomly partitions the dataset, time-series cross-validation preserves the chronological order of the data by sliding a window over past observations and predicting the subsequent periods. This approach allows for a more accurate estimation of a model's predictive capabilities across multiple forecast horizons. When only a single window is used, it resembles a standard train-test split, where the test set consists of the most recent observations, and the training set includes all the prior data. Given the study period spans from January 17, 2018, to December 18, 2024, a total of 2,524 daily observations (approximately 7 years) are available. The first 6 years (85% of the data) are allocated for training, while the final year (15% of the data) is reserved for testing.

To define the forecast horizon based on data frequency, the present study utilizes a daily data frequency. For a one-week forecast, h=7 days, and for a one-month forecast, h=30 days. Another parameter, the step size for advancing the data window, is set to 7 days (one week) or 30 days (one month) depending on the specific forecast horizon. Additionally, the number of prediction windows is fixed at 360 to ensure carrying out a comprehensive evaluation across the dataset.

Model Validation

To evaluate the predictive performance of the models, this study employs four metrics ofRoot Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (SMAPE). These metrics quantify the deviation between predicted and actual values, with lower values indicating a higher predictive accuracy. The mathematical formulations of these metrics are provided below:

$$RMSE = \sqrt{\frac{1}{H}\sum_{\tau=t+1}^{t+H}(y_\tau - \hat{y}_\tau)^2} \tag{12}$$

$$\mathrm{MAE}(y_\tau, \hat{y}_\tau) = \frac{1}{H}\sum_{\tau=t+1}^{t+H}|y_\tau - \hat{y}_\tau| \tag{13}$$

$$MAPE(y_\tau, \hat{y}_\tau) = \frac{1}{H}\sum_{\tau=t+1}^{t+H}\frac{|y_\tau - \hat{y}_\tau|}{y_\tau} \tag{14}$$

$$SMAPE(y_\tau, \hat{y}_\tau) = \frac{1}{H}\sum_{\tau=t+1}^{t+H}\frac{|y_\tau - \hat{y}_\tau|}{|y_\tau| + |\hat{y}_\tau|} \tag{15}$$

Statistical Bases and Descriptive Statistics

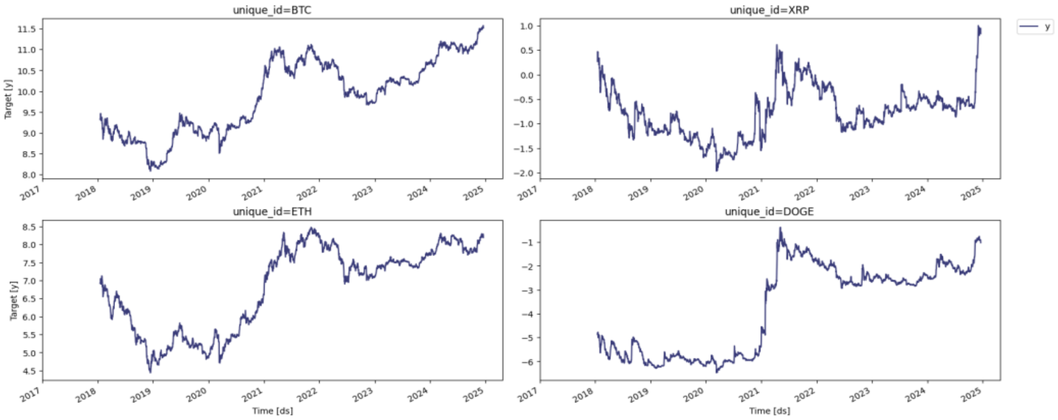
In this study, data from four cryptocurrencies with the highest market capitalization during the period from January 17, 2018, to December 18, 2024, were utilized. Table 1 presents the descriptive statistics for these four cryptocurrencies, while Figure 1 illustrates the trend of changes in their logarithmic price data. 85% of the initial portion of the data was used for training, and 15% of the remaining data was allocated for conducting cross-validation.

Table 1.
Data Descriptive Statistics

	Count	mean	min	25%	50%	75%	max	std
BTC	2524	9.883	8.082	9.095	10.007	10.663	11.573	0.885
DOGE	2524	-3.767	-6.478	-5.854	-2.780	-2.218	-0.379	1.867
ETH	2524	6.794	4.434	5.544	7.290	7.793	8.479	1.164
XRP	2524	-0.767	-1.969	-1.142	-0.745	-0.481	0.998	0.508

(Source: Researcher's Findings)

Figure 1.
The Logarithmic Price Trends of Four Major Cryptocurrencies



(Source: Researcher's Findings)

As evident in the data, both trend-based and cyclical behaviors, alongside stochastic components, are observable in the charts. Subsequently, efforts were made to estimate the models aimed at decomposing these elements within the logarithmic prices of four major cryptocurrencies.

Findings

Initially, three key time-series forecasting methods based on the Recurrent Neural

Network (RNN) approach were selected for conducting a performance comparison. Each model was cross-validated using various hyperparameters (Table 2), and their predictive capabilities were evaluated across three forecast horizons: 1 day, 7 days (one week), and 30 days (one month). As shown in Table 2, the required input size for achieving optimal predictions increases on average across all models as the forecast horizon extends.

Table 2.
Hyperparameters Tuning of three Models at Different Horizons

Time Horizons	Model	Input Size	Batch Size	Encoder Hidden Size	encoder_n_layers	decoder_hidden_size	decoder_layers	learning_rate	max_steps	encoder_dropout
1 day	RNN	30	5	54	2	128	2	0.010	500	0.20
	LSTM	28	5	54	2	128	2	0.015	500	0.15
	GRU	28	5	32	2	64	2	0.015	500	0.15
7 days	RNN	30	5	54	2	128	2	0.010	500	0.20
	LSTM	28	5	54	2	128	2	0.015	500	0.15
	GRU	28	5	32	2	64	2	0.015	500	0.15
30 days	RNN	60	8	54	2	128	2	0.010	500	0.20
	LSTM	60	5	54	2	128	2	0.015	500	0.15
	GRU	50	5	32	2	64	2	0.015	500	0.15

(Source: Researcher's Findings)

Table 3 presents the prediction errors of the three deep learning and neural networks models for different forecast horizons using 360 daily observations (approximately one year). The findings indicated the following:

First: In a short-term forecasting (1-day horizon), the LSTM model performs well in predicting the prices of three cryptocurrencies—DOGE, ETH, and XRP. For BTC price prediction, the performance of LSTM and GRU models is nearly identical, while the RNN model does not demonstrate a superior predictive power for any of the cryptocurrencies.

Second: In a medium-term forecasting (7-day horizon), the GRU model outperforms the others in predicting the prices of all four cryptocurrencies. It is worth noting that the prediction errors, assessed using RMSE, MAE, MAPE, and SMAPE metrics, increase compared to the 1-day horizon, reflecting reduced accuracy with longer forecast horizons.

Third: In a long-term forecasting (30-day horizon): the LSTM model exhibits the best performance in predicting the prices of all four cryptocurrencies. Similar to previous findings, the prediction errors for the 30-day horizon are higher than those for the 7-day horizon, further emphasizing the decline in accuracy as the forecast horizon expands.

Table 3.

Forecasting the Error of the Cryptocurrencies' Prices for Different Deep Learning Models

Horizon = 1 day

crypto	metric	RNN	LSTM	GRU	crypto	RNN	LSTM	GRU
BTC	rmse	0.145	0.110	0.117	ETH	0.217	0.056	0.114
	mae	0.131	0.101	0.099		0.193	0.047	0.108
	mape	0.012	0.009	0.009		0.024	0.006	0.013
	smape	0.006	0.005	0.004		0.012	0.003	0.007
DOGE	rmse	0.309	0.253	0.298	XRP	0.187	0.150	0.21
	mae	0.287	0.229	0.241		0.103	0.064	0.099
	mape	0.151	0.146	0.166		0.172	0.121	0.192
	smape	0.079	0.064	0.069		0.113	0.077	0.122

Horizon = 7 day

crypto	metric	RNN	LSTM	GRU	crypto	RNN	LSTM	GRU
BTC	rmse	0.213	0.186	0.067	**ETH**	0.255	0.267	0.071
	mae	0.189	0.139	0.052		0.213	0.249	0.052
	mape	0.017	0.013	0.005		0.027	0.031	0.006
	smape	0.008	0.006	0.002		0.013	0.015	0.003
DOGE	rmse	0.433	0.524	0.184	**XRP**	0.193	0.264	0.182
	mae	0.388	0.371	0.129		0.127	0.154	0.087
	mape	0.196	0.270	0.09		0.243	0.302	0.197
	smape	0.108	0.098	0.040		0.137	0.168	0.103

Horizon = 30 day

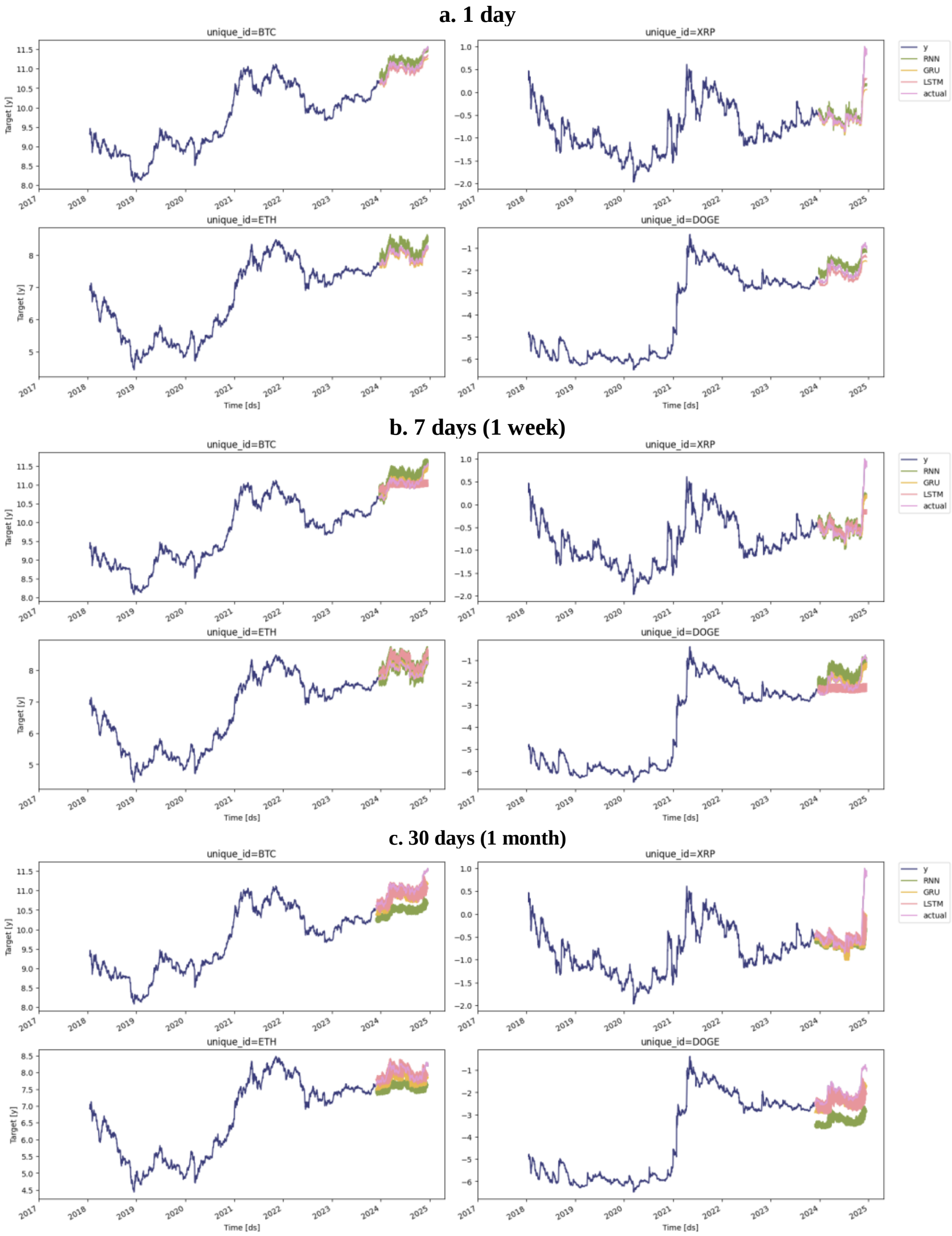
crypto	metric	RNN	LSTM	GRU	crypto	RNN	LSTM	GRU
BTC	rmse	0.558	0.191	0.237	**ETH**	0.425	0.145	0.238
	mae	0.544	0.143	0.211		0.402	0.111	0.207
	mape	0.049	0.013	0.019		0.05	0.014	0.026
	smape	0.025	0.007	0.010		0.026	0.007	0.013
DOGE	rmse	1.277	0.487	0.505	**XRP**	0.272	0.241	0.257
	mae	1.243	0.360	0.43		0.14	0.121	0.126
	mape	0.69	0.227	0.255		0.372	0.306	0.336
	smape	0.242	0.088	0.103		0.124	0.115	0.116

(Source: Researcher's Findings)

Finally, to provide a more detailed assessment of the predictive power of the deep learning and neural network models (RNN, GRU, and LSTM) for the studied cryptocurrencies across 1-, 7-, and 30-day horizons, Figure 2 has been plotted in four separate panels.

Figure 2.

Prediction of the Logarithmic Prices of Four Cryptocurrencies Using Deep Learning and Neural Network Methods for Different Horizons (1, 7, and 30 Days)



(Source: Researcher's Findings)

Discussion and Conclusion

In this study, the performance of different deep learning and neural networks approaches for forecasting the logarithmic prices of four major cryptocurrencies was evaluated. The dataset consisted of daily observations spanning from January 17, 2018, to December 18, 2024. Three models from the RNN family—RNN, LSTM, and GRU—were employed, as they represent some of the most important deep learning and neural networks and AI techniques for time-series forecasting. For the analysis, 85% of the total data (approximately the first 6 years) was allocated for training, while the remaining 15% (approximately the final year) was reserved for testing. Initially, three prominent RNN-based forecasting methods were selected for conducting the performance comparison. These models were then tested across the forecast horizons of 1 day, 7 days (one week), and 30 days (one month), with each being cross-validated under varying hyperparameters. The key findings regarding the model specifications and the comparative performance of three nonlinear deep learning and neural network models (RNN, LSTM, and GRU) are summarized below:

- As the forecast horizon increases, the average input size required for achieving the best predictions rises across all the models.
- In short-term forecasting (1-day horizon), the LSTM model demonstrates a superior performance for DOGE, ETH, and XRP price predictions. For BTC, both LSTM and GRU exhibit a similar performance, while the RNN model lags behind.
- In medium-term forecasting (7-day horizon), the GRU model outperforms the others for all four cryptocurrencies. The prediction errors increase compared to the 1-day horizon, indicating a reduced accuracy with extended horizons.
- In long-term forecasting (30-day horizon), the LSTM model shows the best overall performance for all four cryptocurrencies. Consistent with earlier results, the prediction errors are highest for the 30-day horizon, highlighting the general decline in accuracy as the forecast horizon lengthens.
- The choice of an appropriate deep learning and neural networks method depends on the forecast horizon and data characteristics.

The findings suggested that selecting the right deep learning and neural networks approach is contingent upon the specific forecast horizon and data attributes. Given the superior accuracy of the LSTM model for 1- and 30-day horizons and the GRU model's dominance in the 7-day horizon, it is recommended that investors and financial market participants pay attention to cross-market signaling and profitable strategies. By understanding the inter-market dynamics and leveraging these predictive insights, stakeholders can better manage risks and achieve desirable returns.

Future research could enhance the forecasting accuracy and robustness by exploring hybrid models that integrate deep learning architectures with external factors, such as macroeconomic indicators, social media sentiment, or regulatory changes. Additionally, leveraging advanced architectures like Graph Neural Networks (GNNs) —capable of capturing interdependencies among cryptocurrencies or market entities—could address complex spatiotemporal patterns. These approaches, combined with real-time data streams and interpretable AI techniques, may improve the adaptability to abrupt market shifts and enhance the scalability across diverse forecasting horizons.

These findings provide valuable insights for estimating the mean equation, which is instrumental in forecasting the expected returns of cryptocurrency assets for risk management purposes.

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A Review of Methods for Reducing Hallucinations in Generative Artificial Intelligence to Enhance Knowledge Economy

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ABSTRACT

Generative Artificial Intelligence (AI) models, such as large language models, are transforming various sectors of the knowledge economy, including education, research, development, and data analysis, due to their ability to generate new contents. However, hallucination, which refers to the generation of content that appears plausible but lacks scientific basis, presents a significant challenge to the safe adoption of this technology in critical applications such as financial analysis and market prediction. This study aims to explore the effects of hallucinations on productivity of the knowledge economy and proposes some approaches to mitigate them. Through conducting a systematic literature review and qualitative analysis, different types of hallucinations in generative AI models are identified, and their effects on trust and productivity in knowledge-based systems are examined. The review of hallucination reduction methods indicates that the approaches utilizing reinforcement learning with human feedback enhance the reliability of the generated content by correcting errors in the model's output through repeated adjustments. Finally, this study presents a hybrid approach to hallucination reduction in knowledge economy. This approach is based on three techniques of prompt engineering, retrieval-based generation, and self-improvement through feedback and reasoning. The results provide a foundation for future research on managing AI risks and enhancing the productivity of the knowledge economy.

KEYWORDS

Generative AI, Hallucination, Knowledge Economy, Large Language Models, Trust.

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Introduction

Large Language Models (LLMs) such as GPT-3 (Brown et al., 2020) and ChatGPT have demonstrated remarkable capabilities in generating natural language texts. The ability of these models to provide fluent and comprehensive responses across a wide range of topics has surpassed earlier chatbots in terms of efficiency and performance. Generative AI, which includes deep learning models such as GANs and transformers, has made significant strides in recent years, particularly in the field of knowledge economy. The knowledge economy focuses on production, distribution, and use of knowledge in society. In this section, we highlight some of the impacts of generative AI on the knowledge economy. Generative AI can contribute to enhancing the quality of knowledge. These models can analyze the existing data and identify errors within it, improving the accuracy and credibility of knowledge. Furthermore, generative AI can foster collaboration in knowledge production by enabling people across the globe to work together and generate new knowledge.

Despite the remarkable capabilities of generative AI, these models have a significant flaw known as 'hallucination', which means they produce information that seems logical but is, in reality, inaccurate or meaningless (Gunjal et al., 2023). The encoding of knowledge in large language models is incomplete and the generalization of knowledge may lead to 'memory distortion'. This can result in the generation of incorrect or "hallucinated" information by these models. Hallucination arises when advanced models like GPT-4 and others may produce entirely inaccurate or baseless outputs (Ray, 2023). This problem occurs due to pattern some generation techniques during the training phase and the lack of real-time Internet updates, leading to inconsistencies in the output information (Ray, 2023).

Hallucination, or the 'fabrication of information', is a common failure mode for large language models in which they generate incorrect or meaningless content. In other words, AI hallucinations are also referred to as "self-made" outputs. AI cannot independently verify whether the text it generates is factually accurate or trustworthy. Hallucinations can lead to the spread of misinformation and in applications requiring critical decision-making, may cause harmful consequences or lead to a loss of trust in AI systems.

Generative AI can have various effects on the knowledge economy. These models can assist in the generation of new knowledge, improve the quality of knowledge, increase access to knowledge, and enhance collaboration in knowledge production. However, hallucination in AI presents multiple challenges, including the issues of truth detection, trust, security, and ethics. Therefore, responsible use of this technology is necessary and its challenges must be seriously addressed.

In this context, identifying hallucinations has become a significant concern and researchers have been working to identify the factors contributing to hallucination to propose effective mitigation methods. For instance, researchers have introduced the mFACT method as a tool for detecting hallucinations in summaries, expanding its applicability from English to other languages (Qiu et al., 2023). Furthermore, a framework for identifying hallucinations based on contextual information has been proposed (Li et al., 2023). On the other hand, some researchers offer a different perspective on the causes of hallucinations, investigating contradictions as one of the factors contributing to this issue (Mündler et al., 2023). In terms of reducing hallucination, researchers have proposed effective methods. For example, some have explored retrieval-based generation approaches to address the key challenges of accuracy and timeliness in LLM outputs (Kang et al., 2023), while others have proposed prompt engineering techniques to reduce hallucinations (Farquhar et al., 2024; Peng et al., 2023).

This study aims to examine both the positive and negative effects of generative AI on the knowledge economy and identify the challenges associated with its hallucinations. The central question is how we can harness the capabilities of generative AI while mitigating the negative impacts of its hallucinations. The main questions of this research study are:

1. What effects does the hallucination of Artificial Intelligence have on the knowledge economy?
2. What methods are there to reduce the hallucination of Artificial Intelligence?
3. Which of the methods of reducing the hallucination of Artificial Intelligence is effective in the field of the knowledge economy?

In the following sections, we will first introduce the knowledge economy and its relationship with generative AI. In Section 3, we will discuss the issue of hallucination in generative AI and explore its various forms. Then, after presenting the problem of hallucination in generative AI, we will introduce methods for reducing hallucinations to improve the productivity of the knowledge economy. Finally, Section 4 will present the conclusion and future research directions.

Theoretical Literature

Strengths of Generative AI

Generative AI refers to computational techniques that can create seemingly new and meaningful content, such as text, image, music, or video, from training data. Generative AI systems can not only be used for artistic purposes, such as generating new texts, imitating authors, or creating new images that mimic the style of image makers, but also as intelligent response systems to assist humans (Feuerriegel et al., 2023). In other words, Generative AI refers to deep learning models that can generate original content (not simply copying from their own training data) such as long texts, high-quality images, videos, or realistic sounds, in response to user requests or prompts. Generally, Generative AI operates in three stages:

1. Training: to create a base model.
2. Fine-tuning: to adapt the model to a specific application.
3. Generation, evaluation, and further fine-tuning: to improve accuracy. (Lv, 2023)

Types of Hallucinations in Generative AI

1. Sentence Contradiction: In this case, a large language model produces a sentence that is completely contradictory to the one requested and lacks a subject matter connection. For example:

- Requested sentence: "Write a birthday card for mom".
- Expected response: "Happy Birthday, Mom. I love you".
- AI response: "I am so happy we are celebrating our first anniversary! Looking forward to many more years. With love,"

2. Request Contradiction: This occurs when the language model generates a response that contradicts the user's request and does not align with the subject matter.

For example:

- User's question: "Tell me about the benefits of meditation".
- Expected answer: "Meditation has many benefits, including stress reduction, improved concentration, and emotional well-being".
- AI-generated response (on an unrelated topic): "Meditation goes beyond earthly concerns and opens dimensional portals where your thoughts are shining butterflies guiding you through the cosmic realm of inner peace".

3. Factual Contradiction: In this case, the large language model generates an incorrect response to the user's query and presents it as a fact, which could mislead the user and spread misinformation. For example:

- User's query: "What is the capital of France?"
- Expected answer: "The capital of France is Paris".
- Incorrect AI response: "The capital of France is Zagreb".

4. Irrelevant or Random Hallucinations: This occurs when the large language model generates random information based on the user's query that has no subject connection and is simply a guess. For example:

- User's query: "Can you suggest a good recipe for chocolate chip cookies?"
- Expected answer: "Here's a classic recipe for chocolate chip cookies with step-by-step instructions".
- Random AI response: "The temperature today in Toronto is -2 degrees".

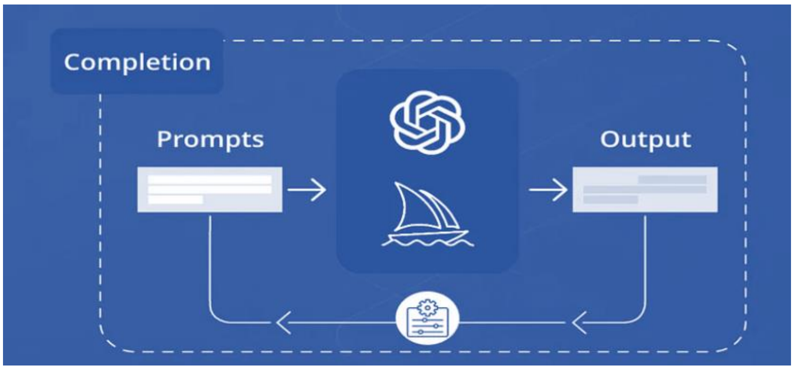
Various methods have been proposed to reduce hallucinations (Kanaani et al., 2024; Köpf et al., 2024; Mardiansyah et al., 2024; Yan et al., 2024). Each of these methods can help generate more accurate and reliable knowledge, thus assisting in providing more precise analyses. In the following section, we will examine the methods of reducing hallucinations in AI in more detail.

Methods for Reducing Hallucination

1. Prompt Engineering Methods

Prompt engineering is the art of crafting suitable inputs for AI models in such a way that they guide the models toward producing more accurate, relevant, and useful responses. This process combines logical thinking, creativity, language, and problem-solving skills. Prompt engineering is a field where, through experimentation and evaluation of different instructions, the goal is to obtain the best possible output from a text-based AI model (White et al., 2023). In terms of reducing hallucinations in model outputs, this process can provide the context and expected results more precisely (Feldman et al., 2023). This process is very similar to coding, but instead of using structured instructions and vocabulary, natural language is employed. While the users have the freedom to use their own language, with that freedom comes great responsibility. A moderate request is likely to result in a moderate outcome. This structure is illustrated in Figure 1.

Figure 1.
Prompt Engineering Structure



(Source: Researcher's Findings)

By structuring the requests made to these models accurately, the likelihood of AI hallucination can be reduced. The main goal for users when utilizing AI is to obtain correct information. Therefore, the trust placed in acquiring information can greatly affect its use. To reduce the occurrence of AI hallucinations, users should consider three basic principles when making requests. These principles are:

1. Use clear and specific requests;
2. Provide examples and samples;
3. Adjust the LLM parameters.

Another prompt engineering-based method recently introduced is the LLM-Augmenter (Peng et al., 2023). This method proposes a system where an LLM is enhanced with a set of Plug-and-Play modules (Li et al., 2023). This system enables the LLM to generate prompts based on external knowledge. Additionally, using feedback generated by performance functions, it iteratively refines the LLM prompts to improve the model outputs. In this paper, the authors introduce the LLM-Augmenter to enhance the LLMs using external knowledge and automatic feedback.

2. Retrieval-Augmented Generation (RAG)

Retrieval-augmented Generation (RAG) systems combine the language model's capabilities with external information sources. The main idea is to retrieve relevant contexts from knowledge bases before generating text, so that the language model's outputs are based on real evidence. RAG enhances the responses of large language models by utilizing external, trusted knowledge bases instead of relying solely on potentially outdated training data or the model's internal knowledge. This approach addresses critical challenges related to the accuracy and timeliness of LLM outputs. (Kang et al., 2023).

A RAG system enhances the language model by integrating factual information obtained from various knowledge sources. This system reduces hallucination by ensuring that all the generated responses have supporting evidence and the model uses this evidence rather than making baseless guesses. If no evidence is found, the system can honestly declare its lack of knowledge. Here are a few examples to better understand how RAG requests work:

Example A: When was the first refrigerator invented?

Answer: 1854: The first working refrigerator was built by James Harrison, a Scottish inventor. His vapor compression refrigeration system paved the way for modern mechanical refrigeration technology.

Example B: Who was the lead actor in the movie Titanic?

Answer: Kate Winslet: She played the role of Rose DeWitt Bukater in the 1997 movie Titanic, directed by James Cameron. Leonardo DiCaprio also starred in the film as Jack Dawson.

In the above-mentioned examples, the system first retrieves relevant facts from a knowledge source, then generates the answer. This ensures that the output is based on the retrieved information, preventing the model from generating unsupported, incorrect facts. **Table 1** outlines the advantages and limitations of RAG. While RAG requests help reduce hallucination through retrieved facts, this technique is most effective when knowledge sources are large, high-quality, and regularly updated. Using multiple complementary knowledge bases can also offer greater flexibility.

Table 1.
Advantages and Limitations of RAG

Advantages	Limitations
Combines external information to reduce hallucination without basis.	Requires large datasets or knowledge bases for retrieving contextual information which can be costly.
Allows the model to return to an "uncertain" state if no contextual data is available.	If the knowledge source contains errors or real gaps, there is a risk of superficially repeating facts without a deep understanding.
Retrieved facts act as a strong signal to stabilize the generated text.	Not easily scalable compared to pure language model approaches.

(Source: Researcher's Findings)

3. Self-Improvement through Feedback and Reasoning

After a large language model generates an output for a specific prompt, appropriate feedback on that output can improve the quality and accuracy of the model's future outputs. In this context, specific techniques have been introduced to reduce errors caused by misconceptions. According to a study by Madaan et al. (2023), LLMs, especially GPT-3, have significant capabilities in few-shot prompting, which enhance their applications in real-world language tasks. However, the issue of improving GPT-3's reliability has not been fully explored. This study divides reliability into four key aspects—generalization, social biases, calibration, and reality—and introduces simple yet effective prompts to improve each aspect. The research surpasses small-scale supervised models in all reliability metrics and provides practical solutions for enhancing GPT-3's performance.

4. CoVe (Chain-of-Verification Prompts)

Chain-of-Verification prompts (CoVe) explicitly ask models to provide step-by-step verification for their responses, citing credible external sources. These prompts are formulated as a series of logically verifiable inferences leading to the final answer. One type of chain-of-verification approach was presented by Si et al. (2022) in response to a user question. The LLM generates a base answer that may include inaccuracies, such as real hallucinations. They demonstrate an example of a question that GPT-3.5 failed to answer correctly.

Literature Review

Knowledge economy refers to an economy in which production and services are based on knowledge and information. In recent decades, the emergence of generative technologies, especially in the fields of AI and machine learning, has had profound and significant impacts on the knowledge economy. The knowledge economy, which is based on the production, distribution, and use of knowledge, is directly related to generative technologies. One of the prominent effects of generative technologies on the knowledge economy is the increase in efficiency and productivity in research and development processes. For example, using machine learning algorithms, companies can analyze large datasets and achieve faster results. Research shows that these technologies can significantly reduce the time required for the development of new products. Another application of generative technologies in knowledge economy is the automatic generation of knowledge through data processing. This can lead to increased efficiency and effectiveness in knowledge management (Alghanemi et al., 2022).

Next, we will examine the relationship between generative AI and knowledge economy more closely, as well as its impacts on various economic sectors.

Innovation and Creativity: Generative AI aids the innovation process by producing new ideas and content. In the knowledge economy, innovation is one of the key factors for economic growth and progress. For instance, designers can use generative AI to create new and innovative designs that help improve products and services (Teimuraz & Goderdzishvili, 2023). This capability not only increases competitive advantages but also fosters a culture of continuous improvement and adaptability in industries, ultimately contributing to economic growth in the knowledge economy.

Cost and Time Reduction: The use of generative AI in processes can significantly reduce the costs and time required for the content production. This means companies can manage their resources more efficiently and, as a result, have more capacity to invest in research and development (Yu & Lai, 2021).

Development of New Products and Services: Generative AI can assist companies in bringing new products and services to the market. For example, in the gaming industry, creating new content using AI can lead to the development of more engaging and diverse games. This, in turn, can increase demand and foster the economic growth (Mayahi et al., 2022).

Personalization of Customer Experience: Using generative AI, companies can offer personalized experiences to their customers. This is due to the AI's ability to analyze the customer data and generate content that aligns with their preferences and needs. Such personalization can lead to increased customer loyalty and sales growth (Ramnarayan, 2021).

While generative AI can contribute to the development of the knowledge economy, it also brings risks of economic inequality. This technology may allow more advanced companies and countries with access to technological infrastructure and skilled labor to benefit more, which could further widen the economic gaps. Additionally, the use of generative AI introduces a series of ethical and legal challenges. For example, the creation of fake or misleading content can damage the credibility and legitimacy of information. Issues related to intellectual property and data usage must also be addressed. Furthermore, generative AI could lead to the reduction of traditional jobs. As AI increases productivity and efficiency, some traditional jobs might be affected and they will disappear. This creates a need for retraining and skill adaptation to help the workforce adjust to the new changes.

Another major challenge in the field of generative AI is the hallucination in large language models, which leads to the generation of seemingly correct but actually incorrect information, posing significant risks to the knowledge economy. We will review different types of hallucinations in AI.

Methodology

This article aims to investigate the impact of hallucinations in generative AI on the knowledge economy. Given the novelty of the field of hallucinations in generative AI, some relevant articles have been published in recent years. In this study, an attempt has been made to review all credible articles in this field systematically. Accordingly, Scopus, Google Scholar, Science Direct, and IEEE databases were searched using the keywords "artificial intelligence", "hallucination", and "knowledge economy". After an initial review, 50 articles were selected for a comprehensive review, and 15 articles were identified and selected for more in-depth analysis.

Findings

According to the reviews, the methods of illusion reduction that can be useful for productivity in the knowledge economy have been identified and the results are shown in Table 2. These studies show how different techniques can increase the accuracy and reliability of these models and, as a result, provide more accurate and practical analyses in the knowledge economy.

Table 2.
A Summary of Research Studies on Hallucinations in Large Language Models and their Impact on the Knowledge Economy

Authors	Insights	Conclusions
Yuji et al., 2024	The paper discusses how hallucinations in large language models, termed "knowledge overshadowing," can lead to over-generalization, resulting in inaccurate outputs. This undermines the reliability of knowledge-intensive tasks, affecting decision-making and trust in AI-generated information across various sectors.	• Knowledge overshadowing causes hallucination in language models. • Training data imbalance increases hallucination rates and impacts the model performance.
Ma et al., 2024	The paper does not specifically analyze the economic consequences of illusionary errors in large language models. It focuses on their error detection capabilities and the development of the Critical Calculation and Conclusion prompt to improve reliability in solving unreasonable math problems.	• LLMs can detect unreasonable errors but struggle with content generation. • CCC template improves the error detection and correction in LLMs.
Saxena et al., 2023	The paper highlights that hallucinations in large language models can lead to a loss of credibility and trust among users, particularly in critical fields like healthcare, education, and finance, ultimately affecting the economy of knowledge by undermining reliable information dissemination.	• The framework enhances the transparency and credibility of LLM responses. • The framework improves the accuracy and faithfulness of LLMs in drug-related inquiries.
Amayuelas et al., 2023	The paper does not specifically analyze the economic consequences of illusionary errors in large language models. Instead, it focuses on understanding LLMs' knowledge, measuring uncertainty, and addressing known-unknown questions to mitigate hallucinations.	• The study investigated capabilities of Large Language Models (LLMs) in understanding their own knowledge and measuring uncertainty. • It proposed a novel categorization scheme to elucidate the sources of uncertainty in known-unknown questions.
Bian et al., 2023	The paper highlights that false information in large language models (LLMs) can lead to global detrimental impacts, authority bias, and in-context pollution, ultimately challenging the reliability and safety of LLMs, which affects the economy of knowledge.	• False information spreads and contaminates memories in large language models. • Current large language models are susceptible to authority bias.

(Source: Researcher's Findings)

The review of hallucination reduction methods in the literature indicates that the approaches utilizing reinforcement learning with human feedback enhance the reliability of generated content by correcting errors in the model's output through repeated adjustments (Madaan et al., 2023; Tu et al., 2024; Vima et al., 2024). Based on the identification of various types of hallucinations in generative AI, this research attempted to propose a method that can reduce these types of hallucinations in the knowledge economy domain to produce and analyze accurate information. The proposed method is a hybrid approach based on three hallucination reduction techniques ofprompt engineering, retrieval-based generation, and self-improvement through feedback and reasoning. The proposed method is outlined step-by-step as follows:

1. Define the Question Clearly:

Formulate the question in the knowledge economy domain clearly and specifically.

a. Identify the key terms and concepts.
b. Define the scope and range of the response.

In the field of knowledge economics, it is crucial to precisely define specific terms and concepts to prevent misunderstandings and delineate the scope of inquiry. This involves clarifying the issues which should be addressed and excluded by the research question. For instance, instead of a broad question like "what is the role of technology in the economy?", a more focused question such as "what is the impact of information technology on economic growth in developing countries?" can be posed. In this refined question, key terms like "information technology," "economic growth," and "developing countries" are explicitly defined, thereby establishing clear boundaries for the response (Schulhoff et al., 2024).

2. Retrieve Relevant Information:

Use credible and reliable sources within the knowledge economy domain (e.g., scholarly articles, government reports, statistical databases) (Molina & Chicaíza, 2011)

a. Retrieve information related to the question using the identified key terms and concepts.
b. Evaluate the information based on the source credibility, publication date, and accuracy.

3. Prompt Engineering:

Design the prompt in such a way that guides the AI model to use the retrieved information (Lo, 2023). This involves crafting questions that are direct and focused, ensuring the AI can effectively utilize the data to generate relevant and insightful responses. In order to maximize the effectiveness of your inquiry, it is essential to establish a clear framework for analysis. This includes specifying the particular aspects of the knowledge economy you wish to explore, such as innovation, human capital, or digital transformation.

c. Use appropriate linguistic structures to direct the model (e.g., "based on the following information, ...").
d. Summarize and structure the retrieved information in the prompt and provide it to the model (Khamassi et al., 2024).

4. Generate the Response:

The AI model generates the response using the prompt and retrieved information. In this phase, the AI model leverages advanced algorithms and natural language processing techniques to analyze the retrieved information and generate a response that answers the research question (Feuerriegel et al., 2023)

5. Evaluation and Revision:

Evaluate the generated response for accuracy, completeness, and clarity. This iterative process allows for refining the inquiry and enhancing the quality of insights derived from the AI model, ultimately leading to a more nuanced understanding of the complex dynamics within the knowledge economy. This iterative process enables the continuous improvement of inquiries, ensuring that insights gained from the AI model are not only accurate but also deeply informative and relevant to current trends in the knowledge economy. If necessary, revise the prompt and repeat steps 3 and 4 to obtain the desired response.

Discussion and Conclusion

As discussed in this research study, hallucination is recognized as the biggest obstacle to safely deploying powerful models in systems that impact people's lives. Therefore, the widespread adoption of large language models in practical environments depends heavily on resolving and mitigating hallucinations. To enhance the productivity of the knowledge economy using generative AI, it is essential to identify methods for reducing hallucinations. The knowledge economy involves optimizing the use of existing knowledge and information within a society or organization.

In this study, the issue of hallucinations in large language models, one of the tools of generative AI, was examined, and methods for reducing them were explored. Mitigating hallucinations in generative models for the knowledge economy leads to the production of accurate and up-to-date information. As a result, organizations can develop new products and services that better align with market needs and customer demands. Among the methods for reducing hallucinations, prompt engineering and self-improvement through feedback and reasoning are powerful tools that, by reducing hallucinations and enhancing the accuracy of information, can contribute to the productivity of the knowledge economy. These processes enable organizations and societies to make the best use of the existing knowledge while also generating new knowledge.

Accordingly, in this research study, a hybrid method based on prompt engineering, information retrieval, and feedback for generating accurate information using generative AI in the context of the knowledge economy was presented. Given the growing importance of generative AI and its role in knowledge production, it is recommended that researchers and developers pay greater attention to identifying and mitigating hallucinations in large language models. To this end, the following suggestions are noteworthy:

1. Further Research on Identifying Hallucinations: To improve the accuracy and reliability of large language models, more research is needed to identify and classify different types of hallucinations. Specifically, developing automated methods and algorithms to effectively detect hallucinations in model outputs should be prioritized.
2. Developing New Techniques to Address Hallucinations: Researchers should focus on developing advanced techniques to mitigate hallucinations. One proposed approach could involve using feedback systems that update language models based on the user inputs, thereby reducing errors in model outputs. Additionally, prompt engineering strategies can have a significant impact on reducing hallucinations.
3. Training Users to Use Generative Models Responsibly: Given that hallucinations

can lead to misleading information, users should be trained on how to use these models responsibly and how to identify incorrect or ambiguous outputs. This training could include warnings about the risks and challenges associated with using generative models.

4. Enhancing Transparency and Reliability of Models: An important recommendation is to enhance transparency in the design and training of the generative models. By improving transparency, users and researchers can gain a better understanding of the decision-making processes of models, thereby reducing the risk of hallucinations.

5. Further Study on the Impact of Hallucinations on Critical Decision-Making: It is essential to study the impact of hallucinations in large language models on critical decision-making, particularly in fields such as healthcare, law, and economics. These studies can help identify best practices for using models in these areas and mitigate risks arising from incorrect information.

6. Advances in AI Policy and Ethics: Researchers and policymakers should focus on developing ethical principles and legal frameworks for the use of generative AI. These principles could include responsible management of generated information, data ownership rights, and accountability for false information.

7. Future-Proofing and Continuous Model Updates: Continuous updating of large language models based on new data can help reduce hallucinations. Attention to up-to-date data and the use of appropriate scheduling methods for model updates can improve the accuracy and reliability of the generated results.

Finally, it is recommended that future researchers develop more comprehensive models in the area of hallucination reduction, specifically aimed at improving the knowledge economy. These models should be designed to reduce hallucinations in order to enhance the quality of knowledge produced for the knowledge economy. Additionally, creating regulatory frameworks for managing the generated content and developing assessment tools to detect and correct false information in this area is of critical importance.

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Shaping Fintech through Regulations: Insights and Future Directions

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ABSTRACT

Regulations regarding financial technologies (fintech) refer to laws that aim to balance financial innovation with the maintenance of security, transparency, and financial stability in digital markets. This research study aims to analyze the trends, challenges, and future directions in the field of fintech regulations using a Bibliometric approach. To this end, relevant keywords were initially searched in Scopus and Web of Science databases, resulting in the selection of 191 papers as the research dataset. Subsequently, the *Bibliometrix* package in R was employed to identify the influential authors and institutions, analyze temporal trends, and detect the related research clusters. The results indicated that research on fintech regulations has shown a significant growth. Core challenges in this field include maintaining data security, achieving international regulatory coordination, and facilitating the acceptance of financial innovations. Ultimately, this study provided some insights into the challenges of regulating innovation and offered guidance for researchers, policymakers, and fintech professionals in understanding the current trends and designing more effective regulatory frameworks to support the financial innovation.

KEYWORDS

Bibliometric Analysis, Financial Regulation, Fintech, Regulatory Challenges, Trend Mapping.

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Introduction

Financial technologies (fintech) significantly shape the landscape of financial innovations and customer service delivery. In this context, regulating fintech, which aims to balance innovation and consumer protection, has emerged as a major challenge in policymaking and developing this sector. Given the rapid growth of fintech, regulatory frameworks must evolve alongside the technological advancements to ensure compliance without impeding the innovation. This article analyzes this dynamic field by examining key trends, challenges, and future research avenues.

In recent years, the emergence of regulatory technologies (RegTech) and the use of adaptive regulatory frameworks, such as regulatory sandboxes, signify the regulators' efforts to keep pace with the rapid developments in fintech (Nanda, 2024). Nevertheless, challenges like balancing innovation with regulation, effectively implementing sandboxes, and managing emerging risks still require special attention (Chaturvedi & Sinha, 2024).

This article employs a Bibliometrics approach to examine trends, challenges, and future research directions in fintech regulation. This study aims to offer a comprehensive framework for understanding the complex interactions between technological innovations and regulatory requirements. In this context, the role of RegTech in improving compliance processes, the significance of global regulatory frameworks, and the necessity for future research in financial inclusion and risk management will be explored (Igbinenikaro & Adewusi, 2024; Kou et al., 2024).

Given the dynamism of this field, this article emphasizes the need for an ongoing dialogue among regulators, the industry, and researchers to create a sustainable and innovative financial ecosystem. In this research study, we analyze the role of regulations in advancing financial technologies by using a Bibliometrics approach (Nourahmadi, 2024). The main goal of this study is to provide a comprehensive picture of the trends related to regulation in the fintech domain, identify the existing challenges, and explore the future of this field.

1. Temporal and Geographic Distribution:
   - What has been the trend of scientific publications in the field of financial technologies and regulations over the years?
   - Which countries contribute the most to the production of articles related to fintech and regulations?
2. Key Authors and Sources:
   - Who are the most prominent authors in this field, and how is their impact assessed?
   - Which journals have published most of the articles related to financial technologies and regulations?
3. Topics and Keywords:
   - What are the most frequently used keywords in articles related to regulations and financial technologies?
   - Which topics have demonstrated the most significant growth in recent years?

- Providing insights for future foresight and the development of effective regulatory frameworks in the field of financial technologies.

4. Analysis of Thematic Relationships:
   - How do topics related to fintech regulations interact with each other?
   - Which subfields in this context have received the most attention?
5. Identifying Research Gaps:
   - What gaps exist in the research literature concerning fintech regulation and financial technologies?
   - What topics could pave the way for future research?
6. Foresight:
   - What are the future trends in research related to financial technologies and regulations?
   - What challenges and opportunities are anticipated in the development of new regulatory frameworks?

This study, utilizing trend analysis and Bibliometrics Method tools, contributes to a better understanding of the role of regulations in the development of financial technologies and provides new horizons for future research in this area.

Literature Review

Financial technologies (FinTech), recognized as an emerging term, are driven by a set of developing frontier technologies. It encompasses a series of new business models, novel technology applications, and new products and services that significantly impact financial markets and the delivery of financial services. This subject has attracted widespread attention due to the following benefits: increased operational efficiency, effective reduction of operational costs, disruption of existing industry structures, elimination of industrial boundaries, facilitation of strategic disintermediation, creation of new gateways for entrepreneurship, and accessibility to financial services for all individuals (Agarwal & Zhang, 2020; Cao et al., 2020; Loubere, 2017; Nourahmadi et al., 2022; Philippon, 2016; Contreras Pinochet et al., 2019; Rasti et al., 2021; Suryono et al., 2020; Wang et al., 2021). Key technologies in financial technologies include Internet Technology (including the Internet and the Internet of things) (Ruan et al., 2019), Big Data (Chen et al., 2017; Gai et al., 2018a, Nourahmadi et al., 2023), Artificial Intelligence (AI) (Belanche et al., 2019), distributed technology (Blockchain and Cloud Computing) (Belanche et al., 2019; Chen et al., 2019; Gomber et al., 2018; Fosso Wamba et al., 2020), and security technology (Biometric Technology) (Fosso Wamba et al., 2020). Under the influence of these technologies, the traditional model of financial industry has transformed.

Furthermore, researchers have conducted studies that encompass theories and applications. To examine the adoption and use of financial technologies (FinTech) from the perspective of technology acceptance, Singh et al. (2020) proposed a research framework to which substructures of the Technology Acceptance Model were added (Li & Xu, 2021). The fintech ecosystem—including fintech startups, technology developers, the government, financial customers, and traditional financial institutions—was introduced by Li and Xin (2021).

The fintech ecosystem, propelled by digital innovation and collaborative networks, has revolutionized global financial services through using disruptive business models such as peer-to-peer lending, robo-advisory platforms, and blockchain-based payment systems. This paper explores the symbiotic components of the fintech ecosystem, evaluates the strategic investment approaches using real options theory, and addresses the critical challenges—including regulatory compliance, cybersecurity, and technology integration—shaping the future of finance for stakeholders worldwide.

1. The Fintech Ecosystem

The fintech ecosystem comprises five interdependent components (Diemers et al., 2015):

- Fintech Startups: Innovators in payments, lending, and wealth management that unbundle traditional services (Walchek, 2015). Examples include PayPal (payments) and Betterment (robo-advising).
- Technology Developers: Provide infrastructure such as Blockchain, AI, and Cloud Computing. These tools enable startups to scale affordably (Lee et al., 2018).
- Government: Regulators balance innovation incentives with consumer protection. Singapore's payment regulations exemplify proactive policymaking (Lee et al., 2018).
- Financial Customers: Millennials and SMEs drive adoption, prioritizing convenience and low fees (Lee et al., 2018).
- Traditional Institutions: Banks and insurers collaborate with startups via venture capital and incubators to retain competitiveness (Accenture, 2016a).

2. Fintech Business Models

Six dominant business models illustrate the fintech's diversification:

- Payment Systems: Mobile wallets (Apple Pay) and peer-to-peer (P2P) platforms (Venmo) reduce costs and enhance accessibility (Li, 2016).
- Wealth Management: Robo-advisors (Wealthfront) use algorithms to offer low-fee portfolio management, disrupting traditional advisory services (Lee et al., 2018).
- Crowdfunding: Platforms like Kickstarter (rewards-based) and AngelList (equity-based) democratize funding for SMEs (Mollick, 2014).
- Lending: P2P lenders (Lending Club) bypass banks by connecting borrowers directly with investors, leveraging data analytics for risk assessment (Zhu et al., 2012).
- Capital Markets: Fintechs like Robinhood offer commission-free trading, while foreign exchange platforms (Xoom) reduce cross-border transaction costs.
- Insurance: Insurtech firms (Ladder) use telematics and IoT to personalize premiums and streamline claims (Drummer et al., 2016).

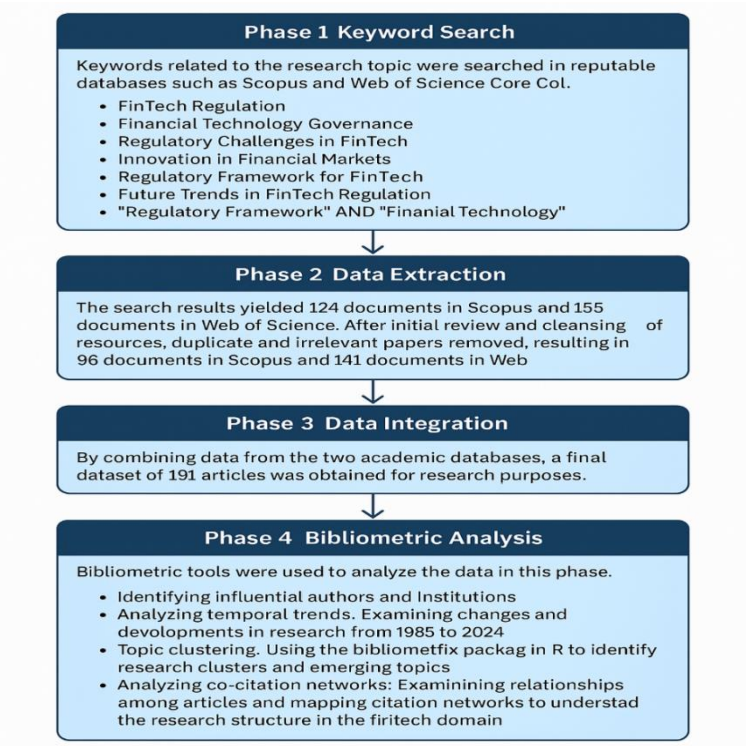
This evolution of laws and regulations in fintech highlights the importance of adapting and forecasting regulations to support innovation while maintaining security, transparency, and financial stability in digital world. These transformations can create new opportunities for advancement in this area, but they also come with various challenges that require innovative and coordinated solutions to be addressed.

Methodology

This research study aims to analyze the trends, challenges, and future directions in the field of fintech regulation through the application of Bibliometric methods. Among the various methodologies available for collecting and analyzing data in academic research (Danaeefard et al., 2014; Danaeefard et al., 2015; Farazmand et al., 2019; Mostafazadeh & Sadeghi, 2014; Mostafazadeh et al., 2016; Sadeghi et al., 2017; Sadeghi et al., 2024), Bibliometric analysis stands out as a systematic and quantitative approach to examining large volumes of scientific literature. This method enables researchers to uncover patterns in publication trends, identify the most influential authors and journals, trace the evolution of research topics, and map intellectual structures within a given field. Bibliometric tools also allow for the clustering of thematically related studies, revealing key areas of scholarly focus and potential research gaps (Nourahmadi et al., 2021; Rasti et al., 2024). By applying this methodology to fintech regulation, this study aims to provide a comprehensive overview of the existing academic landscape and offer insights into its future development.

This analysis was conducted in several phases that are detailed as follows:

Figure 1.
Research process in FinTech domain



(Source: Researcher's Findings)

This Bibliometric methodology provides a comprehensive overview of the current state of research related to FinTech regulation. It highlights the trends, challenges, and future research opportunities in this field. In the following section, the results obtained from the bibliometric software analysis are presented.

Data Analysis

Table 1 provides a comprehensive descriptive overview of the research conducted in the field of FinTech regulation. This descriptive analysis reflects the gradual growth and increasing academic attention to FinTech regulation from 1980 to 2025.

A total of 191 documents were identified, including journal articles (108), books and book chapters (24), and conference papers (5). This indicates the widespread attention this area has received in scientific journals and academic resources.

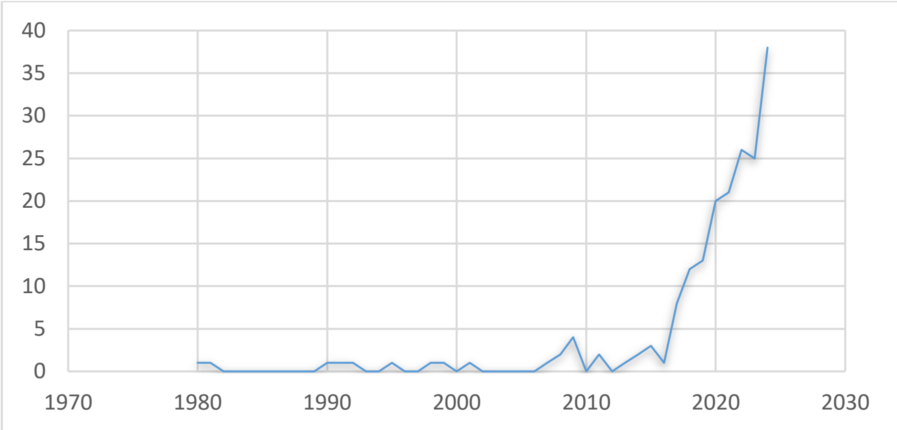
Most of the articles have been written collaboratively, with an international collaboration rate of 17.8%, demonstrating extensive global interactions in this research domain. Moreover, an annual growth rate of 2.47% and an average of 9.12 citations per document indicate the significant impact of research in this field.

Table 1.
Descriptive Statistics of the Conducted Research Studies

Descriptive	Results
Main Information About Data	
Timespan	1980:2025
Sources (Journals, Books, etc)	151
Documents	191
Annual Growth Rate %	2.47
Document Average Age	5.71 year
Average citations per doc	9.12
Document Contents	
Keywords Plus (ID)	303
Author's Keywords (DE)	424
Authors	
Authors	389
Authors of single-authored docs	68
Authors Collaboration	
Single-authored docs	76
Co-Authors per Doc	2.21
International co-authorships %	17.8
Document Types	
article	108
book	9
book chapter	15
conference paper	5
review	4

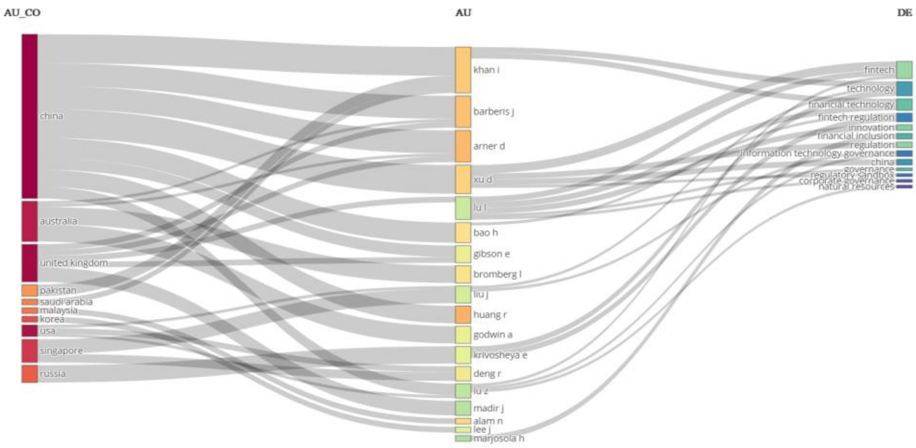
(Source: Researcher's Findings)

Figure 2.
The Trend of Scientific Publications over Different Periods



(Source: Researcher's Findings)

Figure 3.
The Research Communication Network in the Field of Financial Technologies



(Source: Researcher's Findings)

This diagram comprehensively displays the connections between various countries, authors, and research topics in the field of financial technologies. It consists of three main axes, each representing a part of the scientific communication network in this area.

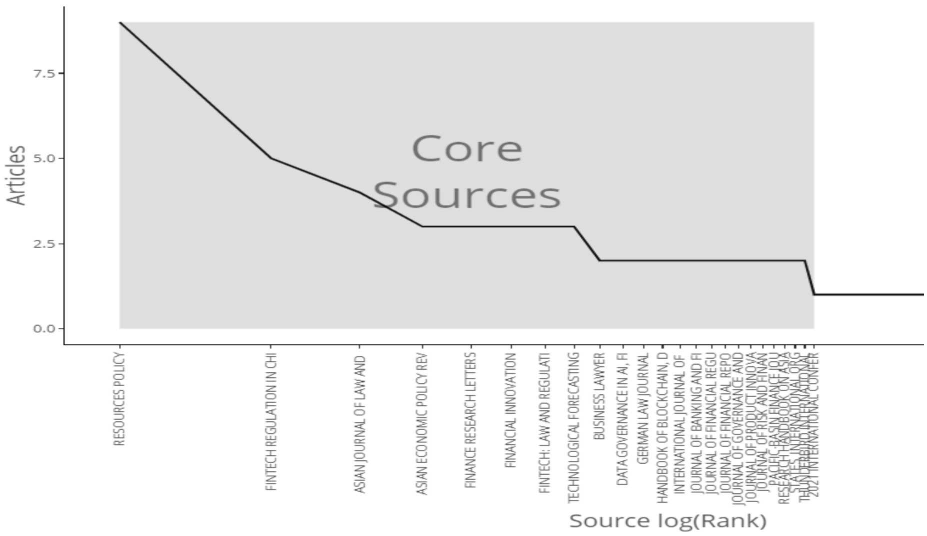
The axis of countries of origin (AU_CO) in this diagram illustrates the countries with the highest number of contributions to research related to financial technologies. In particular, China, Australia, and the United Kingdom play significant roles in advancing this research line. China, as a pioneer in this field, has attracted considerable attention, indicating a high concentration of researchers in financial technologies. Other countries also participate in this field, but their priorities and focuses on various topics differ.

The author axis (AU) represents the research activities of researchers in different countries. Authors are categorized based on their country and research topics in this axis. The colors and sizes of the boxes in this axis are directly related to the intensity of activities and the level of participation of each author in various research areas related to financial technologies. This section helps to identify the key contributions of authors compared to other researchers in different fields.

The axis of research topics (DE) analyzes the main topics of research, which include FinTech, Technology, and FinTech Regulation. These topics represent emerging trends in the field and the challenges in the development of financial technologies. The thickness of the connecting lines between the countries and different topics indicates the intensity and focus of research on these subjects, with thicker lines signifying higher attention and concentration of researchers on that particular topic.

Ultimately, this diagram provides an accurate and comprehensive image of international collaborations and research trends in the field of financial technologies. It helps researchers and decision-makers identify strengths and opportunities for conducting research in new areas, thereby proposing better strategies for developing this area.

Figure 4.
The Scientific Sources according to Bradford's Law



(Source: Researcher's Findings)

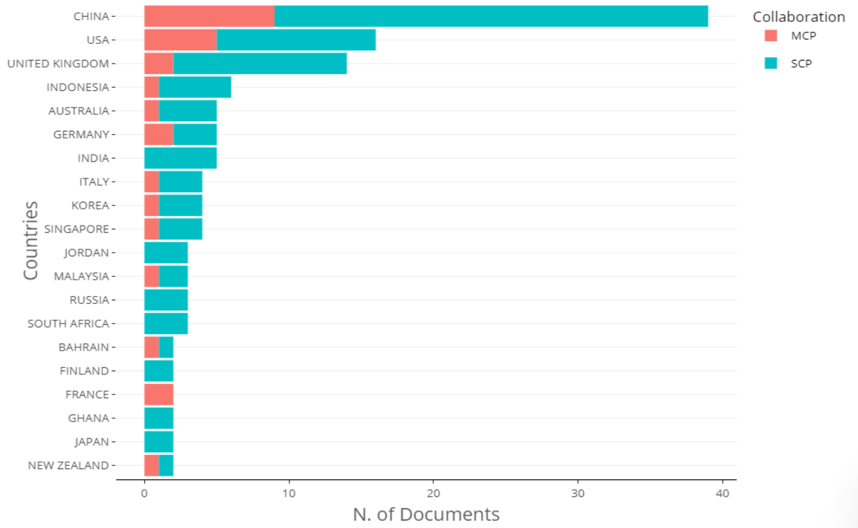
The diagram based on Bradford's Law displays the distribution of scientific articles from various sources, assisting in identifying key resources in a specific research area, such as financial technologies. This diagram consists of two main axes: the vertical axis (Y) representing the number of published articles and the horizontal axis (X) ranking sources or scientific journals based on their number of publications. The sources are arranged from the most to the least utilized based on the number of published articles.

In this analysis, the central area of the diagram, shown in gray colour, represents "Core Sources", which include key publications and journals in the field of financial technology. These sources play a crucial role in developing research and advancing knowledge in the field.

The article distribution in the diagram shows a downward trend as one moves away from core sources, indicating that only a few journals published most of the articles, while many others published only a few. This highlights the importance of core sources and their dominant role in research.

The conclusion emphasizes that in any research area, including financial technologies and regulations, a limited number of sources act as key resources. Identifying these sources can help researcher's access credible articles and guide future studies, ultimately improving research quality and effectiveness.

Figure 5.
Corresponding Author's countries



(Source: Researcher's Findings)

Figure (5), Analysis of Article Distribution Based on the Countries of Corresponding Authors The article distribution chart based on the countries of corresponding authors provides important insights into the scientific contributions of different countries in a specific research field and highlights international collaborations. The vertical axis represents the countries of the corresponding authors, while the horizontal axis shows the number of articles published by authors from each country, reflecting their scientific output in the field. This analysis reveals that China leads significantly in scientific production, followed by the United States, indicating their dominant roles in the field. The United Kingdom and Indonesia also show notable contributions, ranking next.

The chart also distinguishes between types of collaboration. Articles with multiple-country collaborations (MCP) are marked in red, representing cross-border scientific interactions, while those published independently within a single country (SCP) are shown in blue, making up the majority of each country's scientific output. These distinctions help identify patterns of global collaboration and scientific networks.

The data analysis shows that leading countries like China, the U.S., and the U.K. primarily publish articles domestically. However, countries such as Germany and Australia, while also producing domestic articles, have significant international collaborations, reflecting their active scientific networks and knowledge exchange.

In conclusion, the analysis underscores the key roles of China and the U.S. as scientific leaders and the importance of international collaboration in advancing knowledge. Identifying these patterns helps researchers and policymakers better understand collaboration opportunities and design strategies to expand global scientific networks.

Table 2.
The Frequency of the Most Important Keywords Used in the Articles

Frequency	Terms
48	fintech
15	regulation
13	innovation
12	financial
12	financial regulation
8	financial technology
8	governance
7	financial inclusion
7	financial innovation
7	technology

(Source: Researcher's Findings)

Figure 6.
The Keyword Cloud of the Most Frequently Used Articles

(Source: Researcher's Findings)

The word cloud diagram is a useful tool for analyzing the frequency distribution of words and key concepts in scientific texts and articles related to finance and technology topics. This diagram visually represents the importance of various concepts through word size, with more frequently occurring words appearing larger and more prominent. In analyzing this diagram, the following points can be considered:

Keywords Analysis

- *FinTech*: Positioned at the center of the word cloud with the largest size, this keyword reflects the high significance of the concept in financial technology research. FinTech is not only a crucial term in financial industry but also represents a broad and innovative field of technologies that have transformed financial services and practices.
- *Financial Regulation / Governance*: These keywords also appear prominently in the word cloud, indicating that legal frameworks and regulatory issues are among the key topics in FinTech research. In particular, the challenges related to aligning new technologies with existing legal and regulatory frameworks remain a critical concern.
- *Innovation*: This keyword stands out clearly, emphasizing the central role of innovation in FinTech industry, which is consistently marked by rapid changes in the delivery of financial services.

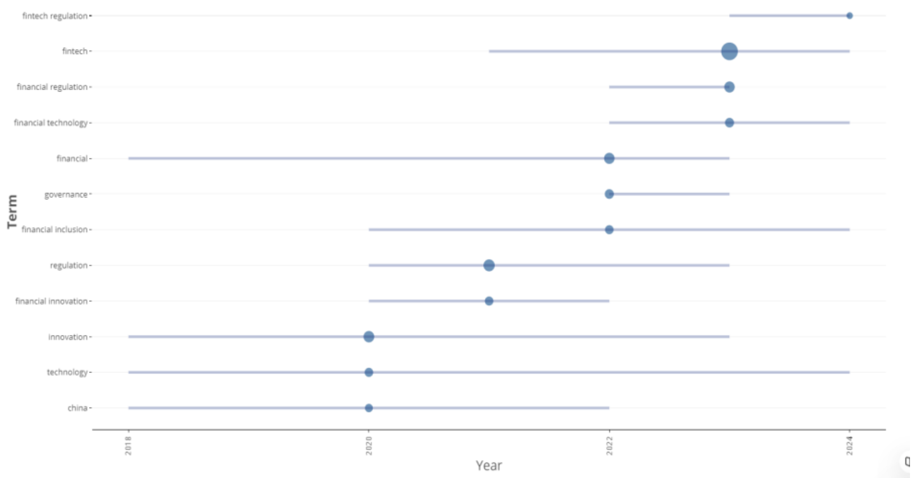
Other Related Concepts

- *Financial Services and Financial Technology*: These keywords also appear prominently in the word cloud, highlighting the core services and technologies that lie at the heart of the transformations driven by FinTech.
- *Regulatory Sandbox*: This term refers to experimental environments that allow for the testing of financial innovations, particularly regulatory compliance and the adaptation of new technologies to existing laws.
- *Inclusion and Performance*: These keywords highlight the growing importance of financial inclusion and performance evaluation within new technologies. "Inclusion" refers to providing broader access to financial services, while "Performance" focuses on the effectiveness and efficiency of these services.

Key Points

- Keyword Frequency: The size and clarity of keywords in the word cloud indicate the frequency of their appearance in the analyzed articles. Larger words represent concepts that have been discussed more extensively in the literature.
- Conceptual Linkages: The simultaneous presence of keywords like *Regulation* and *Governance* alongside *FinTech* reflects the strong interconnection between regulatory topics and financial technologies. These terms represent essential themes in the study of FinTech and their development within regulatory frameworks.

Figure 7.
The Analysis of the Trend of Financial-related Topics in Recent Years



(Source: Researcher's Findings)

The provided diagram illustrates the evolution of financial-related topics over the years, aiding in a better understanding of changes and research priorities in this field. This analysis can assist researchers, policymakers, and those interested in finance in identifying key trends and significant developments.

1. Emerging Topics:

- *FinTech Regulation*: The need for regulatory frameworks is growing due to the rapid expansion of FinTech and new business models. This is essential to ensure the financial stability and manage the emerging risks.
- *FinTech*: The continuous evolution of FinTech highlights the increasing role of advanced technologies in financial services, with global impacts.

2. Sustainable Topics:

- *Financial Technology*: Ongoing discussions emphasize the impact of technology on financial sectors, with FinTech continuing to evolve as a key area of research.
- *Financial Regulation*: The focus on legal frameworks ensures the stability and transparency of financial systems, underlining the importance of regulatory oversight.

3. Innovative Topics:

- *Financial Innovation*: Innovation in financial products and services, driven by FinTech, is central to the industry's progress.
- *Financial Inclusion*: Efforts to reduce inequality and improve access to financial services, especially in developing countries, remain crucial to global financial systems.
- *Financial Governance*: There's an increasing focus on transparency, accountability, and performance evaluation within financial systems.

4. Innovation and Technology:

- *Innovation and Technology*: Advances in data processing, AI, and Blockchain are foundational to new developments in financial industry.

5. Geographical and Political Contexts:

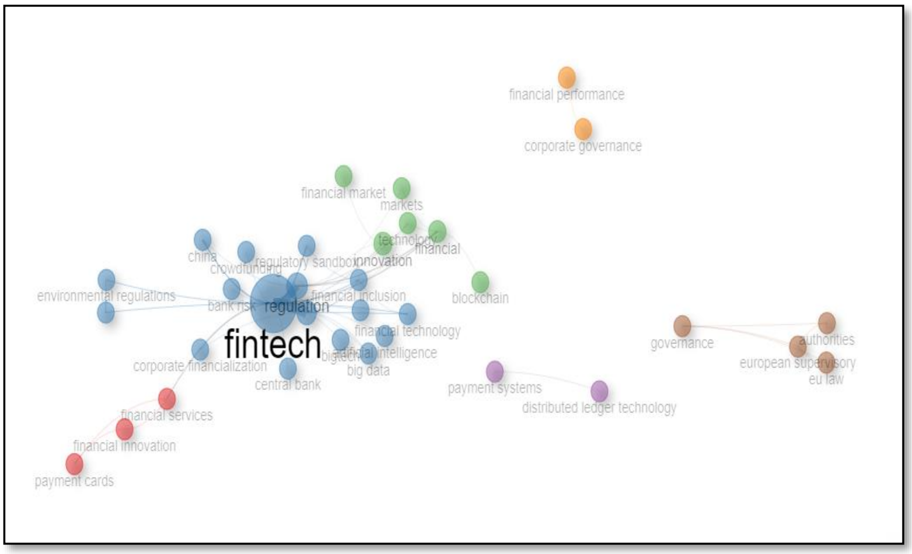
- *China*: China's significant role in FinTech innovations positions it as a leader in the global financial technology landscape, driving trends that other nations follow.

Conclusion:

- *Legal Aspects*: Growing attention to FinTech regulation highlights the need for new laws and improved oversight mechanisms to keep pace with technological advancements.
- *Sustained Innovation*: Innovation remains a key driver of the FinTech industry, influencing the financial services and business models.
- *Geographical Influence*: Countries like China are shaping global FinTech trends through their rapid adoption of new technologies, setting examples for others to follow.

This analysis provides valuable insights for researchers and policymakers regarding the current trends in financial sectors.

Figure 8.
A Co-Word Network Map



(Source: Researcher's Findings)

The co-occurrence network diagram illustrates the interconnected relationships between key terms in the FinTech and financial sectors, highlighting how concepts in these fields interact and influence one another. Here's an analysis of the diagram:

Core Node:

- *FinTech*: FinTech is the central and most influential node, reflecting its dominant role in financial innovation and discussions. It connects to various related terms, emphasizing its widespread impact on industry.

Groupings of Terms:

- *Regulation and Innovation*: Terms like "regulation" and "sandbox innovation" are closely linked to FinTech, suggesting a focus on balancing technological advancements with legal frameworks.
- *Technology*: Terms such as "financial technology" and "big data" highlight the financial sector's emphasis on leveraging new technologies for more efficient, transparent, and intelligent services.

Other Key Elements:

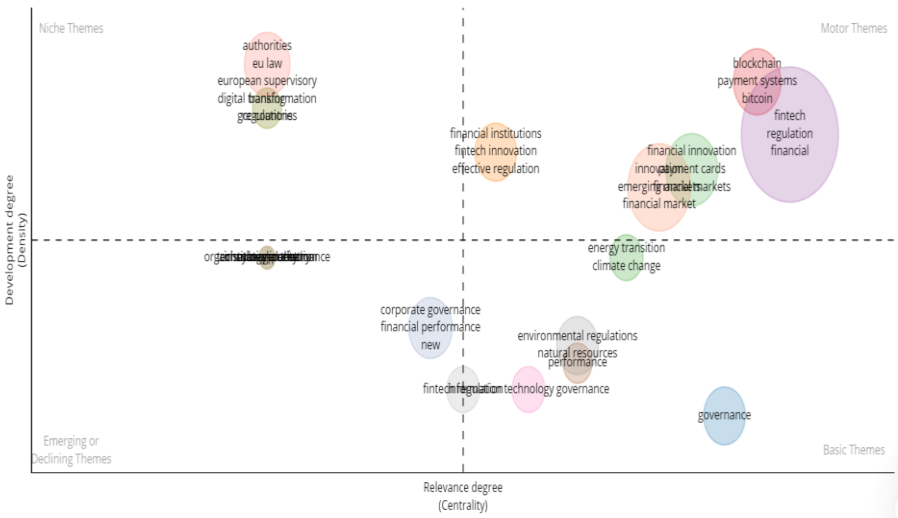
- *Financial Inclusion and Markets*: These terms are directly connected to FinTech, underscoring the importance of inclusive financial services and their impact on global markets.
- *China*: As an independent node in the network, China represents a significant geographical and political impact on financial innovations and FinTech. With its rapid adoption of new technologies and supportive policies, China is a major player in the FinTech industry.

Other Nodes:

- *Financial Performance and Corporate Governance*: Positioned on the right side of the diagram, these nodes emphasize the macro-level and regulatory aspects. They are crucial in FinTech as regulatory systems and performance evaluations directly influence the development and stability of financial technologies and innovations.
- *European Regulatory and Legislative Bodies*: Located in another section, these nodes reflect the importance of legal and regulatory frameworks in FinTech. Regulatory organizations like the European Union play a key role in developing and standardizing international regulations for FinTech activities.

The co-occurrence network illustrates the complex and interrelated relationships between FinTech and financial terms. It highlights how innovation, regulation, and technology are intertwined, shaping the development of financial industry. FinTech, as the core of this network, continues to expand and influence various financial sectors. Analyzing these connections can help researchers, policymakers, and professionals gain a better understanding of the current trends and challenges ahead in FinTech and finance.

Figure 9.
The Thematic Map of Keywords



(Source: Researcher's Findings)

The presented thematic map is designed to visualize and analyze the trends in financial and technological sectors. It helps identify the relationships and importance of various topics. Here's an overview:

Explanation of the Axes:

1. *Vertical Axis (Development/Density)*: This axis shows the level of development and density of each topic. Well-established topics like "FinTech" and "Blockchain" are at the top, while emerging or declining topics, such as "Authorities" and "Digital Transformation", are at the bottom. This axis helps track emerging and fading trends.

2. *Horizontal Axis (Relevance/Centrality)*: This axis represents the relevance and centrality of topics. Foundational topics like "Governance" are on the left, while engine topics like "FinTech", "Blockchain", and "Payment Systems" are on the right, reflecting their significant impact on innovation and transformation.

Topic Categories:

1. *Upper Topics (Upper Section)*: These are specialized and less recognized topics with narrower scopes, such as "Authorities", "EU Law", and "Digital Transformation".
2. *Engine Topics (Right Section)*: Central topics driving change and innovation, including "FinTech", "Blockchain", and "Payment Systems", have a significant influence on industry.
3. *Foundational Topics (Left Section)*: Essential topics like "Governance" and "Corporate Governance", which shape the foundational principles of financial and regulatory activities.

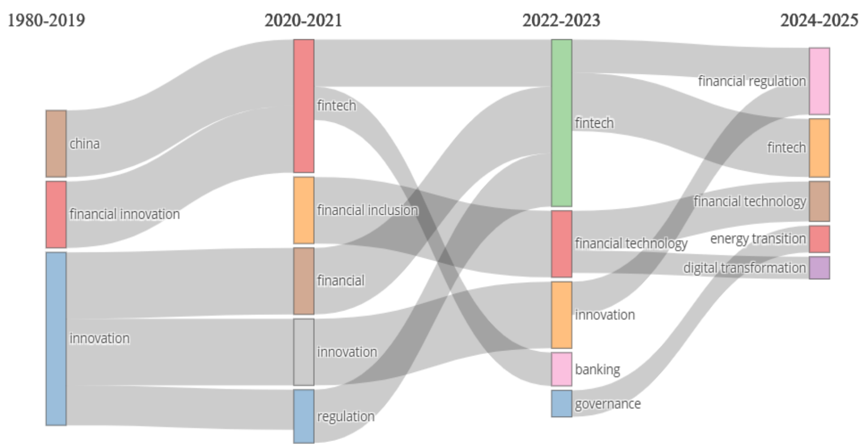
Key Observations:

1. FinTech and Regulation: Central and evolving topics like "FinTech" and "Regulation" are key drivers of change in financial industry.
2. Financial Innovation: Both engine and niche categories highlight the importance of innovation in shaping the financial landscape.
3. Environmental Topics: Issues like "Climate Change" and "Energy Transition" intersect with finance, reflecting the growing focus on sustainability.

Implications

This map provides a dynamic view of the evolving financial and technological landscape. It highlights the current influential topics and emerging trends, allowing stakeholders to focus on areas needing further development and innovation. It also serves as a strategic tool for analyzing the markets and identifying new opportunities.

Figure 10.
A Thematic Evolution



(Source: Researcher's Findings)

The map of "Evolution of Topics" illustrates the key trends and developments in the financial and technology sectors from 1980 to 2025. It provides insights into the significant changes over the years. Here's a summary of its key sections:

1. 1980-2019

- *China*: China emerges as a key player in financial and economic development, significantly influencing global trends, particularly in financial innovations.
- *Financial Innovations and H Innovations*: During this period, financial innovations and human-driven innovations laid the foundation for major changes in the financial sector.

2. 2020-2021

- *FinTech*: FinTech rapidly expands, indicating a surge in financial innovations driven by new technologies.
- *Financial Inclusion*: Access to financial services for a broader population becomes a major concern, highlighting the efforts to reduce financial gaps.
- *Innovation and Regulation*: There's an increasing interaction between new innovations and regulatory requirements, especially with the rise of FinTech.

3. 2022-2023

- *FinTech and Financial Technology*: These topics remain central, evolving rapidly with the rise of digital and technological trends in finance.
- *Energy Transition*: This emerging topic reflects the growing concern for environmental challenges and the need for sustainable innovations.
- *Digital Transformation*: Technological advancements in financial systems and banking continue to shape the sector.

4. 2024-2025

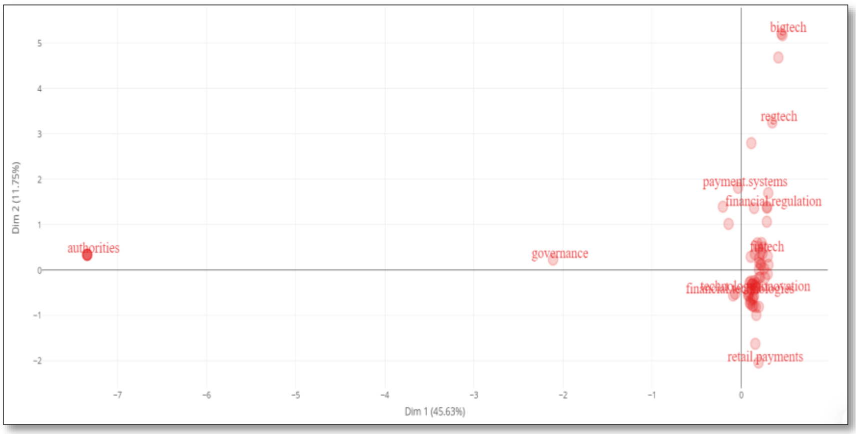
- *Financial Regulation*: Regulation becomes a key focus, with an emphasis on controlling financial activities to maintain system stability and transparency.
- *Financial Technology and Banking*: New technologies in banking, including digital banking, gain an increased importance.
- *Governance*: The need for robust governance structures to ensure financial stability and transparency becomes more pronounced.

Key Takeaways:

- The shift from China and financial innovations in earlier decades to FinTech and digital innovations in recent years is evident.
- New topics like energy transition and digital transformation reflect increasing concerns about the environmental challenges and sustainable solutions.
- The relationship between innovation and regulation is central, highlighting the need for proper oversight amid technological advancements.

This evolutionary map effectively captures the significant transformations in finance and technology, helping stakeholders focus on emerging topics and trends.

Figure 11.
Topic Evolution Map



(Source: Researcher's Findings)

This Principal Component Analysis (PCA) chart effectively analyzes the relationships between several concepts related to financial technology (fintech) and provides a visual representation of patterns and connections in the data. Here is a summary of the key interpretation and findings from the chart:

Interpretation of Principal Components in the Chart

1. Principal Axes:

- The First Dimension (Dim 1): Explains 45.63% of the variance in the data and likely represents overarching themes like technological innovation or its relationship with financial regulations. This dimension highlights the widespread influence of new technologies on financial sector and the need for regulation and oversight in this area.
- The Second Dimension (Dim 2): Covers 11.75% of the data variance, likely focusing on more specific aspects such as the governance structure and regulatory authorities. This dimension may reflect the challenges and opportunities in regulatory frameworks.

3. Key Points:

- Central points like "authorities" and "governance" are located toward the positive side of the second axis, indicating their importance in regulation and oversight, especially in the context of financial technology regulations.
- Points like "fintech", "big tech", and "Regtech" are closer to the first axis, suggesting a greater focus on new technologies and innovations in this domain.

3. Differences and Similarities:

- Proximity of Points: Points that are close to each other indicate strong relationships. For example, if "fintech" and "payment systems" are close, it implies a close interrelationship between these concepts, particularly in financial innovations and payment systems.

- Distance between Points: Points that are farther apart may indicate differences in strategies or topics within the fintech space. This could suggest distinct applications, attitudes, or approaches in the adoption of new technologies.

This analysis helps researchers better understand the complex and interrelated nature of the concepts in fintech. It also serves as a tool for identifying new regulatory opportunities or challenges. Based on these patterns, strategies, innovations, and regulatory improvements can be developed.

Challenges in Regulating Fintech Innovations

This section discusses the key regulatory challenges faced by authorities in adapting to rapid fintech innovations, including the inherent tensions between consumer protection, financial stability, and fostering innovation and competition. The fast pace of technological change demands dynamic and adaptive regulatory approaches (Shapoval, 2020). However, establishing effective regulatory frameworks to balance these conflicting goals is a significant challenge. The complexity of fintech products and services, along with the cross-border nature of many fintech activities, further complicates the regulatory landscape (Ibiyeye et al., 2024).

1. Regulatory Sandbox Approach: Opportunities and Limitations

This part analyzes the effectiveness of regulatory sandboxes as tools for promoting fintech innovation while mitigating risks. Regulatory sandboxes provide a controlled environment for testing innovative fintech products and services under regulatory supervision (Shapoval, 2020). While this approach offers opportunities for real-world learning with minimal risks to consumers and the financial system, challenges include the need for clear guidelines, appropriate regulatory mechanisms, and effective communication between regulators and participants (Ibiyeye et al., 2024). Additionally, the resources required to establish and operate a sandbox can be substantial, potentially limiting access for smaller companies or jurisdictions with limited resources (Masduqie & Santoso, 2023).

2. Concerns regarding Data Privacy and Security in Fintech

This section addresses the regulatory challenges related to data privacy and security in fintech. The increasing reliance on data analytics and AI in fintech raises significant concerns about data privacy and cybersecurity (Ibiyeye et al., 2024). Fintech companies collect and process large volumes of sensitive consumer data, making them targets for cyberattacks and data breaches. Regulators must balance the facilitation of data-driven innovations with consumer privacy protection (Tsapa, 2022). Strong data protection regulations, robust cybersecurity standards, and effective enforcement mechanisms are required. Regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) have been designed to address these concerns but remain challenging to be applied in the rapidly evolving fintech landscape (Islam et al., 2024).

Regulatory Trends in Fintech

1. Emergence of RegTech: Regulatory technology (RegTech) is increasingly used in compliance processes, improving efficiency and reducing operational costs for financial institutions. This trend highlights the growing importance of technological tools in managing regulation and simplifying regulatory compliance (Arner et al., 2017).

- AI and machine learning for analyzing financial data and detecting suspicious activities.
- Blockchain for enhancing transaction transparency and reducing fraud.
- Automated reporting platforms to reduce time and human errors.

2. Global Regulatory Frameworks: Global regulatory frameworks are designed to promote innovation while protecting consumers. These frameworks include protocols like Know Your Customer (KYC) and Anti-Money Laundering (AML), which have been widely adopted across jurisdictions (Zetzsche et al., 2018).

- GDPR standards in the EU focus on data privacy.
- PSD2 regulations facilitate access to banking data for financial service providers.
- International cooperations, such as FATF (Financial Action Task Force), addresse counter-terrorism financing.

Future Research Directions

- Financial Inclusion: Future research should explore the role of RegTech in enhancing financial inclusion, especially in underserved markets. This includes using digital technologies to provide banking services in rural and underserved areas and examining fintech's impact on gender gaps in financial access (World Bank, 2021).
- Risk Management: As fintech evolves, more research is needed on risk management strategies. This includes exploring the risks of AI in financial decision-making, developing regulatory frameworks to manage cybersecurity risks, and assessing fintech's impact on global financial system stability (IMF, 2022).

Conclusion and Recommendations

This paper has explored the rapid advancements and innovations in financial technology (fintech) and their complex interplay with evolving regulatory frameworks. One of the central findings highlights the critical need for aligning technological innovation with effective, forward-looking regulatory strategies. As Fintech, Blockchain, and Regulatory Technology (RegTech) continue to reshape the financial landscape, fostering a coordinated and adaptive regulatory approach becomes increasingly essential. Regulatory authorities must develop flexible, technology-neutral frameworks that not only keep pace with innovation but also ensure consumer protection, financial integrity, and systemic stability.

Looking ahead, future research must address the emerging regulatory gaps within the fintech ecosystem and examine how new regulatory paradigms can be harmonized with the velocity of technological change. Equally important is the cultivation of ongoing dialogue among regulators, industry stakeholders, and academic researchers to foster a collaborative, sustainable, and innovation-friendly financial environment.

Recommendations for Future Research

- *Expanding Data-Driven and Empirical Analyses*: Future studies should incorporate real-world market data and transaction-level evidence to gain deeper insights into the operational challenges, regulatory responses, and transformative potential of fintech innovations.
- *Comparative and Cross-Jurisdictional Studies*: A comparative analysis of fintech regulation across different countries and legal systems can offer valuable perspectives on how diverse regulatory approaches influence innovation trajectories, market entry, and competitive dynamics.
- *Assessing Socioeconomic Impacts*: Investigating the broader social and economic consequences of fintech — particularly its role in promoting financial inclusion, reducing poverty, and expanding access to underserved populations — is essential for shaping inclusive and equitable financial ecosystems.
- *Developing Adaptive Regulatory Models*: There is an urgent need to conceptualize and test new regulatory models capable of keeping pace with the fast-evolving fintech landscape. This includes frameworks for managing data privacy, cybersecurity threats, algorithmic decision-making, and decentralized financial technologies.
- *Addressing Legal and Ethical Considerations*: Future research should delve into the legal, ethical, and normative dimensions of emerging technologies, especially concerning the use of consumer data, algorithmic fairness, accountability, and transparency of Blockchain-based systems.
- *Exploring Innovative Fintech Business Models*: An in-depth examination of novel fintech business models — such as platform-based, data-driven, or collaborative ecosystems — could provide critical insights into market evolution, strategic positioning, and value creation in the digital financial era.

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On the Role of Social Media Analytics in Steering the Digital Transformation of Organizations through Developing Data-driven Dynamic Capabilities

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ABSTRACT

Digital transformation is probably the most attention-grabbing phenomenon in contemporary business-related and managerial discourses. Nowadays, organizations have acknowledged the fruitful impacts of digital transformation on their businesses, so they are trying to implement this transformative journey. However, they have recognized that this is not a short-term project or an easy-going process, so they are struggling to find an appropriate organizational asset to empower them in following this journey appropriately. In this theoretical study, we have introduced social media analytics as such an asset. Accordingly, drawing on the dynamic capability view, we attempted at developing eight propositions and elaborating a theoretical framework in which social media analytics is seen as a great source of data-driven dynamic capabilities (i.e., data-driven environmental scanning, data-driven organizational agility, and data-driven product / service innovation). These propositions are, in turn, positively associated with the main building blocks of digital transformation implementation including digital disruption detection, digital strategy formulation, and digital value creation. Our theoretical framework describes some of the mechanisms through which social media analytics can benefit organizations in steering their digital transformation journey.

KEYWORDS

Data-driven Dynamic Capabilities, Digital Transformation Of Organizations, Social Media Analytics, Theory Building.

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Introduction

Digital transformation has emerged as a critical imperative for organizations striving to remain competitive in today's dynamic business landscape (Nwankpa & Roumani, 2016; Vial, 2019). Despite its significance, the role of social media analytics in steering this transformative journey remains underexplored (Holsapple et al., 2018). This study addresses this gap by proposing a novel theoretical framework that positions social media analytics as a strategic asset for cultivating data-driven dynamic capabilities—specifically, data-driven environmental scanning, data-driven organizational agility, and data-driven product/service innovation—that propel digital transformation. Theoretically, we enrich the dynamic capabilities and digital transformation discourses by delineating how social media analytics uniquely enhances these processes (Teece et al., 1997; Vial, 2019). Practically, we offer managers actionable insights to leverage social media analytics for detecting digital disruptions, formulating digital strategies, and creating digital value, providing a clear roadmap for navigating this journey.

Digital transformation, defined as improving an entity by significantly changing its properties through using digital technologies (Vial, 2019), has become a buzzword in our business world (Hausberg et al., 2019; Talafidaryani & Asarian, 2024; Talafidaryani et al., 2021; Talafidaryani et al., 2023). The recent research has acknowledged that the digital transformation of organizations has positive effects on their performance (Nwankpa & Roumani, 2016; Talafidaryani, 2023) and is a strategic imperative for them to remain competitive in contemporary, constantly shifting, and digitally disrupted business environments (Marx et al., 2021). Today's business environment is increasingly characterized by ambiguity, complexity, stormy changes, and uncertainty (Hafezniya & Ansari, 2024). Accordingly, it is evident that every organization needs to initiate and pursue this transformative journey to benefit from such expected organizational impacts.

However, the problem is that this journey is not a short-term project or an easy-going process in organizations. Instead, the digital transformation of organizations is "an ongoing process of using new digital technologies in everyday organizational life" (Warner & Wäger, 2019, p. 326), which requires some transformative capabilities such as organizational agility as the mechanisms for the ceaseless strategic renewal of the digitally transforming organizations (Warner & Wäger, 2019). In more precise terms, drawing on the notion of dynamic capabilities, digital transformation can be defined as an organization's capacity to "sense and shape opportunities and threats, to seize opportunities, and to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets" (Teece, 2007, 1319). Warner and Wäger (2019) have introduced the digital transformation of organizations as an ongoing process of creating sensing, seizing, and transforming dynamic capabilities for the continuing strategic renewal of the organizations that enables them to constantly benefiting from new digital technologies. Accordingly, the organizations interested in implementing their digital transformation need to possess some powerful assets that empower them to continually build these dynamic capabilities and continuously follow their strategic renewal. For instance, Fasanghari and Asarian (2024) highlight how 5G technology, through prioritized smart tourism projects, serves as a critical infrastructure asset that enhances data connectivity, supporting digital transformation efforts. Similarly, Khodabakhsh et al. (2024) demonstrate that customer knowledge management, mediated by open innovation, strengthens service quality, suggesting a complementary data-driven asset for building dynamic capabilities. However, our current knowledge lacks a comprehensive understanding of these assets, without which organizations cannot initiate and steer their digital transformation journey toward expected outcomes such as performance improvement and competitive advantage.

We do believe that social media analytics, defined as “all activities relating to gathering relevant social media data, analyzing that data, and disseminating findings as appropriate to support business activities” (Holsapple et al., 2018, p. 33), can be considered as one of such assets because of its specific characteristics. First, it is argued that social media data represents a vast and ever-evolving resource for observing human behavior, offering unique possibilities for gaining insights into communities, societies, and individuals (Batrinca & Treleaven, 2015). Accordingly, analyzing such data enables organizations to understand the business events and technological trends in their digitally disrupted business environments effectively which is considered as the initiating point [or probably the most important point] of the digital transformation process (Vial, 2019). Second, the recent studies have introduced social media use as the source of some sorts of dynamic capabilities such as organizational agility (Ye et al., 2022) which are in perfect harmony with the dynamic capabilities required for digital transformation (Warner & Wäger, 2019). Third, the dynamic nature of social media data along with the potentiality of analytics techniques in timely tracing this dynamism allows organizations to see social media analytics as a source for constantly building the dynamic capabilities that is needed for ongoing strategic renewal of organizations in the pursuit of digital transformation (Warner & Wäger, 2019). Accordingly, the current study aims at proposing a theoretical framework in order to describe the role of social media analytics in steering the digital transformation of organizations through data-driven dynamic capabilities. To do so, we rely on the dynamic capability framework (Teece et al., 1997), as one of the most popular theories in strategic management (Heidari & Talafidaryani, 2021) and information systems (Talafidaryani, 2021), and conceptualize the dynamic capabilities enabled by social media analytics as data-driven dynamic capabilities. Also, we see the digital transformation journey of organizations as an ongoing process described by Vial (2019).

This study offers several novel contributions to the literature. First, we propose a pioneering theoretical framework that positions social media analytics as a strategic asset uniquely suited to steer digital transformation by fostering three specific data-driven dynamic capabilities: data-driven environmental scanning, data-driven organizational agility, and data-driven product/service innovation. Unlike prior studies that broadly link social media use to organizational outcomes, our framework delineates precise mechanisms through which social media analytics enhances digital transformation, extending beyond existing literature (e.g., Ye et al., 2022; Warner & Wäger, 2019). Second, we advance the understanding of big data analytics by spotlighting social media data's distinctive role in capability building, a critical yet underexplored aspect of digital transformation. Third, by integrating the dynamic capability view with digital transformation processes, we provide a fresh synthesis that bridges the emerging literatures on analytics-enabled capabilities and digital transformation dynamics, offering a novel lens absent in prior work (e.g., Teece, 2007; Vial, 2019).

Literature Review

Conceptual Background and Theory Development

Social Media Data and Analytics

Social media refers to digital platforms that enable users to generate and exchange content (Kaplan & Haenlein, 2010). Carr and Hayes (2015, p. 50) define social media as "Internet-based channels that allow users to opportunistically interact and selectively self-present, either in real-time or asynchronously, with both broad and narrow audiences who derive value from user-generated content and the perception of interaction with others". Social networking platforms like Facebook, photo and video-sharing sites like Instagram and Pinterest, business and professional networking platforms like LinkedIn, and micro-messaging and news sharing services like Twitter are some examples of social media (De Oliveira et al., 2020).

At the beginning of 2021, active social media users reached 4.20 billion worldwide - more than half of the world's total population. This figure has grown by 490 million (more than 13 percent) compared to the same period in 2020 (Kemp, 2021). As a consequence of this eye-catching reach, social media applications have had ground-breaking implications in different aspects of people's daily lives such as business and commercial life, social and political life, and even learning and educational life (Abed et al., 2015; Alalwan et al., 2016; Alalwan et al., 2017; Algharabat et al., 2017; Hawkins & Vel, 2013; Hinz et al., 2011; Rathore et al., 2016; Usher et al., 2014; Zeng & Gerritsen, 2014; Zhu & Chen, 2015). For example, consumers usually use user-generated comments to review products and services' characteristics, tourists often use social media to define their destinations based on others' ratings, patients generally use these platforms to consult with medical experts and services to facilitate the process of treatment, and students or their parents usually use social media platforms to exchange their opinions about their intended programs and target colleges (He et al., 2015).

Due to such pervasiveness and implications, a huge amount of user-generated content is accessible on social media platforms. In comparison with traditional data, social media data has unique characteristics such as reflecting users' opinions about almost all aspects of their life, being timely and constantly updated by numerous online users, and shaping a metadata with various attributes such as time, locations, users, likes, and dislikes (He et al., 2015). Scholars such as Batrinca and Treleaven (2015) argue that social media data is the biggest, richest, and most dynamic evidence for tracing human behavior that brings some exceptional opportunities for understanding societies, communities, and people.

According to such invaluable characteristics and potentialities of the data available on social media channels, these platforms have gained a remarkable attention in business discourses, and organizations have greatly tried to invest their resources on using social media to support both overall and specific business activities such as marketing and competitive intelligence (He et al., 2015; Orlandi et al., 2020). One of these investments is deploying social media analytics systems in organizations to analyze social media data and implement business intelligence / analytics initiatives. Social media analytics is defined as "all activities relating to gathering relevant social media data, analyzing that data, and disseminating findings as appropriate to support business activities" (Holsapple et al., 2018, p. 33). Drenik (2021) believes that social media is shaping the future of business intelligence / analytics. Social media analytics is related to establishing and assessing some informatics frameworks and tools in order to achieve a specific target application by gathering, scanning, analyzing, summing up, and visualizing social media data (Zeng et al., 2010). In the social media analytics process, social media data is gathered from various platforms, the data is analyzed based on some advanced analytics such as topic modeling, sentiment analysis, opinion mining, trend analysis, and social network analysis, and the results of such analyses are presented in meaningful and insightful ways (Fan & Gordon, 2014).

Data-Driven Environmental Scanning as a Dynamic Capability

According to the discussions provided by De Oliveira et al. (2020), Mention et al. (2019), Orlandi et al. (2020), Song et al. (2021), and Ye et al. (2022), social media empowers organizations to develop the ability of detecting opportunities and threats in their business environments. These scholars argue that social media information enriches organizational activities in obtaining highly desirable insights about emerging technological trends and shifts in customers' demands / needs. This ability that reflects a sensing dynamic capability (Teece, 2007), refers to the ability of environmental scanning. Environmental scanning involves collecting and utilizing information about external events, trends, and connections to support organizational leaders in shaping strategic plans (Aguilar, 1967). Song et al. (2021) uses the term "social media-enabled environmental scanning". However, we prefer to use the term "data-driven environmental scanning" because of our focus on the social media analytics concept grounded in the big social media data and advanced analytics notions.

Social Media Analytics and Data-Driven Environmental Scanning

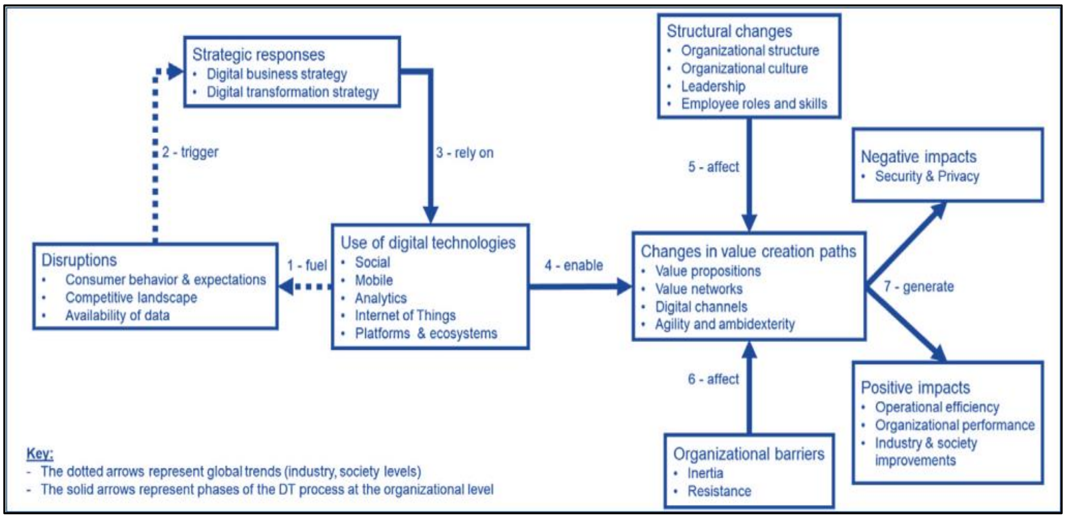
Clearly, this capability relies on analyzing social media data, as simply maintaining a social media presence yields vast user-created content that remains unproductive without the necessary technical and analytical expertise to process its intricate, sporadic, and unorganized nature (Orlandi et al., 2020). In other words, social media-enabled insights can be gained based on advanced big data and business intelligence / analytics technologies (Lau et al., 2012). Therefore, we should say that data-driven environmental scanning is developed by organizations as a consequence of leveraging social media analytics. Accordingly, we propose the following proposition which is also consistent with the recent discussions on the positive association of big data analytics with sensing capability (Wamba et al., 2020) or the positive relationship between business analytics and ecosystem / environmental scanning (Chatterjee et al., 2021; Duan et al., 2020).

Proposition 1 (P1): *The greater social media analytics, the greater data-driven environmental scanning is likely to be.*

Digital Transformation Building Blocks: Digital Disruption Detection, Digital Strategy Formulation, and Digital Value Creation

Digital technologies are described as inherently disruptive technologies (Karimi & Walter, 2015). Therefore, the advent of a new digital technology and its usage bring about some sorts of disruptions for organizations (Vial, 2019). Using disruptive technologies leads to new generations of products / services with new performative attributes that may not be appreciated by the current customers of an organization (Downes & Nunes, 2013; Ganguly et al., 2010). According to the framework proposed by Vial (2019), the digital transformation process is initiated by the disruptions fueled by the use of digital technologies like social, mobile, analytics, internet of things, and platform technologies. In the next step, organizations respond to these disruptions, and this obviously requires being able to sense the disruptions caused by digital technologies. If organizations cannot understand new technological trends and their disruptive consequences, they will not be able to respond to them. And this, in turn, will lead to the inability of organizations in technological opportunism and maintaining their competitive positions in business environments (Orlandi et al., 2020; Srinivasan et al., 2002). Accordingly, the first step for organizations to initiate their digital transformation journey is to develop the required capabilities to appropriately detect digital disruptions.

Figure 1.
Building Blocks of Digital Transformation Process



(Source: Vial (2019))

Data-Driven Environmental Scanning and Digital Disruption Detection

We contend that the ability to conduct data-driven environmental scanning through social media analytics equips organizations to identify digital disruptions effectively. According to Vial (2019), a primary form of disruption driven by digital technologies involves transformations in consumer behavior and expectations. Indeed, digital tools grant consumers widespread access to information and communication channels (Vial, 2019; Yoo et al., 2010), significantly influencing their actions (Chanias, 2017; Hong & Lee, 2017; Vial, 2019). Moreover, these technologies facilitate consumer participation in dialogues between organizations and their stakeholders (Kane, 2014; Yeow et al., 2018), profoundly shaping their expectations for the services organizations should provide (Vial, 2019). Given that social media serves as a powerful platform for consumers to voice their views (Alkhodair et al., 2020; Chang et al., 2019; Choi et al., 2020), the environmental scanning enabled by social media data and analytics allows organizations to monitor shifts in consumer behavior and expectations, a key aspect of digital disruptions. Based on this, we put forth the following proposition.

Proposition 2 (P2): *The greater data-driven environmental scanning, the greater digital disruption detection is likely to be.*

Data-Driven Organizational Agility as a Dynamic Capability

The recent literature has confirmed that there is a positive relationship between social media use and organizational agility (Ye et al., 2022). Organizational agility is generally defined as "an ability to be proactive as well as responsive to changes" (Ketchen & Hult, 2007, p. 574). Organizational agility reflects the organizational capability of sensing the events and changes in the business environment and responding to them in a timely manner in order to effectively and efficiently seizing opportunities and addressing threats (Lee et al., 2015; Overby et al., 2006; Park et al., 2017; Roberts & Grover, 2012; Sambamurthy et al., 2003). The notion of agility has close links to both adaptability and flexibility concepts (Zhang et al., 2022). Some researchers such as Christopher and Towill (2001) conceptualize organizational agility with regard to the adaptability notion, and some others such as Teece et al. (2016) consider agility as an approximate synonym for flexibility. It should also be noted that in contrast to these perspectives, there are some other scholars like Lee (2004) and Swafford et al. (2006) who try to distinguish these concepts from each other. Previous literature has introduced different types of organizational agility. As a case in point, Lu and Ramamurthy (2011) defined market capitalizing agility and operational adjustment agility, or Sambamurthy et al. (2003) introduced customer agility, partnering agility, and operational agility. Although previous studies have introduced various conceptualizations and different types of organizational agility based on the theoretical frameworks adopted by them, almost all of them have tried to reflect some ways to effectively sense changes in market environments and effectively respond to them to seize business opportunities (Park et al., 2017). As one of the best exemplars of this conclusion, we can refer to the Roberts and Grover (2012) that defines the organizational agility notion as the ability of a firm in sensing and responding swiftly to customer-related market opportunities in order to innovate and act competitively and accordingly, introduces two types of agility including sensing agility and responding agility.

In the current study, we adopt the conceptualization of organizational agility proposed by Park et al. (2017) because we believe that this conceptualization is an extended and improved version of previous ones and better supports our research foci and context. Park et al. (2017) considers organizational agility as a manifested type of dynamic capability (Teece et al., 2016), and drawing on the information-processing view of organizations (Daft & Lengel, 1986; Daft & Weick, 1984; Galbraith, 1973; Morgan, 1986; Thomas et al., 1993), they introduce three types of agility including sensing agility, decision making agility, and acting agility as strategic tasks of organizational sense-response process. According to the conceptualization proposed by Park et al. (2017), sensing agility is concerned with acquiring information about business events and changes that may have effect on the organization's performance, competitive advantage, and strategy such as shifts in consumer preference and the advent of new technologies; decision making agility is related to understanding and interpreting the acquired information in the form of opportunities and threats and subsequently, formulating an action plan for benefiting from the identified opportunities and avoiding the perceived threats in business environments; and acting agility is concerned with reconfiguring organizational resources and business processes based on the formulated acting plan with the aim of initiating new competitive activities like lunching new products / services in the market. According to the discussions provided by Park et al. (2017), an agile organization should be able to timely perform a constellation of these tasks to capture opportunities in the business environment.

Social Media Analytics and Data-Driven Organizational Agility

Ye et al. (2022) suggest that utilizing social media boosts organizational agility by facilitating instantaneous exchange, gathering, and synthesis of information via its function as a communication channel (Dellarocas, 2003). This capability allows organizations to demonstrate flexibility in accessing current information and promptly identifying opportunities and challenges among diverse stakeholders (Weber & Tarba, 2014). Consequently, we propose that social media analytics, as an embodiment of social media utilization encompassing three core functions—data collection, processing, and interpretation (Fan & Gordon, 2014)—is positively linked to organizational agility, or more precisely, data-driven organizational agility. Supporting this view, Park et al. (2017) found that business intelligence and communication technologies play a significant role in fostering organizational flexibility. Clearly, social media serves as a communication medium. Furthermore, Choi et al. (2020), through their review of studies on social media analytics-driven business intelligence, highlight the diverse applications of social media data in business intelligence efforts. Additionally, Park et al. (2017) note that certain features of business intelligence and communication technologies align closely with the operational aspects of social media and its analytics, such as real-time information sharing with partners, identifying and visually presenting data trends, and notifying organizations of market shifts while offering robust tools for analysis. Based on these insights, we put forward a proposition that aligns with recent research affirming the positive connection between big data analytics, business intelligence, and various forms of organizational agility (Chen & Siau, 2020; De Medeiros & Maçada, 2021; Ghasemaghaei et al., 2017; Hajli et al., 2020; Hyun et al., 2020; Shirazi et al., 2021; Wang & Ali, 2021; ZareRavasan, 2021).

Proposition 3 (P3): *The greater social media analytics, the greater data-driven organizational agility is likely to be.*

Data-Driven Organizational Agility and Digital Transformation Building Blocks

The digital transformation literature introduces organizational agility as one of the most essential capabilities needed for organizations to digitally transform themselves (Verhoef et al., 2021). Verhoef et al. (2021) argues that organizational agility enables firms to continuously sense and seize the market opportunities provided by new digital technologies. By possessing this capability, organizations become capable to respond to the altering customer demands and the advent of new digital technologies based on constantly reconfiguring and modifying the existing organizational resources, i.e., organizational assets and capabilities. As a consequence, firms will be able to alter their traditional ways of doing business by lunching new products / services and establishing novel digital business models / digital value creation logics.

Accordingly, we do believe that the data-driven organizational agility enabled by social media analytics has a positive impact on the main building blocks of the digital transformation process described by Vial (2019). As discussed before, the organizations interested in initiating their digital transformation journey should be able to detect the digital disruptions fueled by the introduction of new digital technologies (Vial, 2019). Data-driven sensing agility enables these organizations to do so because this capability is concerned with acquiring information about strategic business events and changes such as the advent of new technologies and the shifts in consumer needs (i.e., disruptions) (Park et al., 2017) that are well reflected in social media data and can be well revealed by analyzing this data. In the next step, the organizations engaged in their digital transformation processes should strategically respond to the detected digital disruptions by formulating their digital business strategy and digital transformation strategy (Vial, 2019) both of which are considered as digital strategy in the current study. Data-driven decision-making agility empowers these organizations to achieve this because the decision-making agility capability is responsible for understanding the detected information about the environmental events and changes (i.e., the disruptions) and interpreting them in order to formulate an action plan (e.g., a strategy) aimed at capturing the opportunities and addressing the threats (Park et al., 2017). Next, the organizations in the pursuit of digital transformation change their value creation paths such as value propositions and value networks by creating new digital values (Vial, 2019). Data-driven acting agility enables these organizations to do so because this capability is concerned with modifying organizational resources and business processes based on the formulated acting plan (i.e., the strategy) with the aim of initiating new competitive activities like lunching new products / services in the market (i.e., delivering new sorts of values to the customers) (Park et al., 2017). Accordingly, we propose the following propositions.

Proposition 4 (P4): *The greater data-driven organizational agility, the greater digital disruption detection is likely to be.*

Proposition 5 (P5): *The greater data-driven organizational agility, the greater digital strategy formulation is likely to be.*

Proposition 6 (P6): *The greater data-driven organizational agility, the greater digital value creation is likely to be.*

Data-Driven Product / Service Innovation as a Dynamic Capability

Social media has remarkably grabbed the attention of innovation research in recent years (Bhimani et al., 2019; Testa et al., 2020). In the pertinent literature, there are numerous studies like Alhaimer (2021), De Oliveira et al. (2020), Hassani et al. (2021), Mpandare and Li (2020), Papa et al. (2018), and Salim et al. (2020) in which the researchers have tried to support the positive link between social media use and different types of innovation in organizations. In 2019, Bhimani and his colleagues performed a systematic literature review on social media-innovation interactions, and as a result, they discussed that considering social media as enabler and driver of innovation is the most prominent paradigm in this discourse (Bhimani et al., 2019). In a similar vein, in 2020, Testa and her colleagues conducted a literature review on social media-based innovation, and accordingly, they mapped the discourse to a framework based on two main actors including the seeker of innovation and the provider of innovation and three main questions including why, how, and what that are respectively about determinants, activities, and outcomes (Testa et al., 2020).

Social media enhances the relationships of firms with employees and stakeholders as well as their collaborations with each other (Hoffman & Fodor, 2010; Jorge et al., 2020; Leonardi et al., 2013; Sharma & Bhatnagar, 2016). Therefore, knowledge management, exchange of experiences and ideas, and knowledge sharing are facilitated among the internal and external organizational actors (Ali et al., 2020; Benitez et al., 2018; He et al., 2015; He et al., 2017) that, in turn, will improve the innovation performance of organizations (Benitez et al., 2018; Kim et al., 2011). Social media gives organizations the opportunity of becoming aware of technological trends, competitors' actions, and customer needs (Itani et al., 2017). Also, by relying on social media, organizations will be able to obtain new knowledge from customers and recognize creative ideas with regard to the business environment that can lead to new product / service development (He et al., 2015; He et al., 2017; Martini et al., 2014; Roch & Mosconi, 2016). In this regard, it is interesting to note that there are some studies such as He and Wang (2016), Mention et al. (2019), and Mount and Martinez (2014) in which the scholars have tried to clarify and explain the role of social media use in the process of open innovation defined as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Chesbrough, 2006, p. 1). In this regard, Lindegaard (2014) discusses that social media can support open innovation with regard to key aspects of better communicating with organizational partners, generating new ideas and receiving feedbacks on the current ideas, understanding the business ecosystem (i.e., business intelligence), identifying new assistants for innovation, and promoting innovation outcomes and capabilities. In the current study, we consider product / service innovation (i.e., new product / service development) as our focus on innovation because most of the companies use social media for this type of innovation (Roberts & Piller, 2016). However, we know that social media can support all types of innovation (Aral et al., 2013; Bhimani et al., 2019) as well as all stages of innovation process (Muninger et al., 2019). It is worth noting that in the capability literature, innovation is considered as a dynamic capability (Ganesh & Marathe, 2019; Perdomo-Ortiz et al., 2006; Saenz et al., 2012).

Social Media Analytics and Data-Driven Innovation in Products and Services

According to Moe and Schweidel (2017), social media analytics offers companies a lens into consumer preferences, capturing customer perspectives that drive marketing insights and significantly enhance product and service innovation. In recent years, several studies have explored social media analytics methods to support organizations in developing new products and services. For instance, Khodabakhsh et al. (2024) demonstrated that managing customer knowledge improves service quality through open innovation, indicating that incorporating customer insights—similar to those obtained from social media data—into innovation processes can strengthen data-driven product and service advancements. A notable example is Jeong et al. (2019), who devised an analytical framework leveraging social media mining tools, such as topic modeling and sentiment analysis, to identify opportunities for new product development. These findings underscore a positive connection between social media analytics and innovation in products and services. We refer to this as data-driven product and service innovation, as it stems from social media data and sophisticated analytical methods. Based on this, we put forward a proposition that aligns with the broader association between business intelligence, big data analytics, and innovation (Božič & Dimovski, 2019; Eidizadeh et al., 2017; Ghasemaghaei & Calic, 2020; Maghrabi et al., 2011; Niebel et al., 2019).

Proposition 7 (P7): *The greater social media analytics, the greater data-driven product / service innovation is likely to be.*

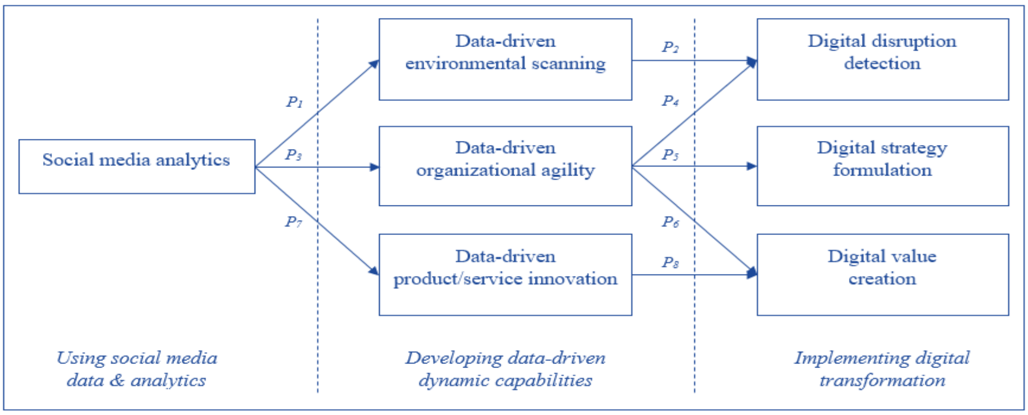
Data-Driven Product / Service Innovation and Digital Value Creation

In the digital transformation process (Vial, 2019), after detecting digital disruptions and formulating digital strategies, the digitally transforming organizations are attempted at changing their paths of value creation by leveraging digital technologies that is called digital value creation in the current study. In this regard, the organizations try to change their value propositions as one of the main ways of changing the current value creation paths (Vial, 2019). For example, Khodabakhsh et al. (2024) illustrate how customer knowledge management, mediated by open innovation, enhances service quality, providing a parallel mechanism whereby social media-derived insights can refine value propositions and bolster digital value creation. According to the discussions provided by Osterwalder et al. (2014), designing a value proposition means finding a way to create products / services that customer's want. This is exactly what data-driven product / service innovation enabled by social media analytics can give organizations. This data-driven dynamic capability has roots in social media data that is one of the richest sources for gaining insights about consumer needs. Hence, this capability empowers firms to develop new products / services or innovate their existing products / services in a way that meets what exactly customers want, i.e., an appropriate value proposition. Accordingly, we propose the following proposition. It is worth noting that in the current research, data-driven product / service innovation is positively associated with digital value creation from two aspects: first, this capability is grounded in social media analytics which is a digital technology according to the SMACIT framework describing the different categories of digital technologies (Sebastian et al., 2017). Therefore, our discussion implies using a digital technology (i.e., social media analytics) to propose new values. Second, data-driven product / service innovation enables firms to establish new value propositions with regard to every digital technology that has had disruptive effects on consumer behavior because this capability has roots in social media data, and this data can reflect such shifts in customer behavior.

Proposition 8 (P8): *The greater data-driven product / service innovation, the greater digital value creation is likely to be.*

Figure 2 depicts our theoretical model based on the developed propositions. This model shows how using social media data and analytics is a great asset to steer the digital transformation journey of organizations by developing some data-driven dynamic capabilities that, in turn, are positively associated with digital transformation implementation.

Figure 2.
The Theoretical Framework



(Source: Researcher's Findings)

Discussion and Conclusion

This study advances the field by proposing a novel theoretical framework that elucidates how social media analytics uniquely steers organizational digital transformation through the development of three data-driven dynamic capabilities: environmental scanning, organizational agility, and product/service innovation. Grounded in the dynamic capability view (Teece et al., 1997) and Vial's (2019) digital transformation process, our framework departs from prior work by specifying how social media analytics, beyond generic big data analytics, enables organizations to detect digital disruptions, formulate digital strategies, and create digital values. This integration not only extends the theoretical discourse on dynamic capabilities (e.g., Warner & Wäger, 2019), but also offers a distinct contribution by linking social media analytics to the full spectrum of digital transformation implementation, an area underexplored in existing literature. In our view, this is one of the possible mechanisms through which social media analytics can help organizations to direct their digital transformation journey. It is interesting to say that based on the proposed theoretical framework, we can conclude that data-driven organizational agility plays a central role in the digital transformation journey of organizations.

Implications

Our theoretical framework delivers distinct theoretical and practical implications. Theoretically, it enriches the dynamic capabilities literature by positioning social media analytics as a pivotal driver of data-driven dynamic capabilities—environmental scanning, agility, and innovation—that uniquely propel digital transformation, extending beyond prior general analytics studies (e.g., Wamba et al., 2020). Practically, it equips managers with a strategic blueprint to harness social media analytics for detecting digital disruptions, crafting responsive digital strategies, and innovating digital value propositions, thereby clarifying its practical value in steering organizational digital transformation.

For practitioners, our framework offers a roadmap for leveraging social media analytics, as a strategic asset, in digital transformation journeys. Organizations struggling with the complex and ongoing nature of digital transformation can benefit from understanding how social media analytics enables the detection of digital disruptions, formulation of appropriate digital strategies, and creation of new digital value. Specifically, managers should recognize that investing in social media analytics capabilities is not merely a marketing decision but a strategic imperative that can fundamentally enhance their organization's ability to sense, seize, and transform in response to digital disruptions.

The central role identified for data-driven organizational agility has particular implications for organizational structure and leadership. Organizations aiming to succeed in digital transformation should cultivate agility across their sensing, decision-making, and acting processes. This suggests a need for flatter hierarchies, cross-functional teams, and leadership that embraces data-driven decision-making and rapid experimentation. Moreover, our framework highlights that social media analytics should be integrated across organizational functions rather than isolated within marketing or communications departments.

To elaborate more on the practical relevance of our theoretical framework, a real case in which social media analytics has been used to steer a digital product transformation could be noted here. In line with our propositions on the contribution of social media analytics to data-driven product/service innovation and, subsequently digital value creation, Jeong et al. (2019) have leveraged a social media mining approach built on topic modeling and sentiment analysis of social media data related to the Samsung Galaxy Note 5 (SGN5) to identify the opportunities for the product's further improvements.

Future Research

One of the limitations of our endeavor is that we have developed the theoretical framework only relying on the bright sides of social media analytics. However, it is necessary to consider the dark sides too. As a case in point, we should note that the low quality of social media data would be an important issue. In fact, if an organization wants to benefit from the total affordances of social media analytics, it should rely on credible social media data. As another case in point, algorithmic biases would be another significant problem that needs attention. Accordingly, social media data quality and algorithmic fairness or accountability would be considered as some moderators to address such limitations of the theoretical framework.

This theoretical investigation opens several avenues for future research. First, we recommend empirical studies to test our propositions across diverse industries (e.g., retail, healthcare) and organizational contexts (e.g., SMEs vs. large firms), using quantitative methods such as surveys to validate the links between social media analytics, data-driven dynamic capabilities, and digital transformation building blocks, along with qualitative case studies to explore contextual nuances. Second, future research should examine potential moderators influencing our framework's relationships, such as organizational culture (e.g., adaptability vs. rigidity) or market turbulence (e.g., stable vs. volatile environments), to identify boundary conditions and enhance practical relevance. Third, we propose investigating ethical considerations tied to social media data use for strategic decision-making, including privacy risks, consent issues, and biases in data representation, to ensure the responsible application of our framework. Additionally, exploring the dark side of social media analytics, such as algorithmic biases, over-reliance on digital signals, or reactive decision-making, could balance its opportunities and risks. Finally, longitudinal studies tracking the evolving interplay between social media analytics and digital transformation amid rapid technological advancements would keep our framework dynamic and feasible.

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A Feasibility Study on the Application of Artificial Intelligence in Central Bank Monetary Policies: Money Creation and Liquidity Management in Focus

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ABSTRACT

In the contemporary economic landscape, the implementation of monetary policies constitutes one of the primary responsibilities of central banks, aimed at objectives such as money creation, liquidity management, inflation containment, and recession prevention. With the emergence of advanced technologies, Artificial Intelligence (AI) has gradually evolved into a powerful instrument for enhancing the efficiency and effectiveness of these policies. The adoption of intelligent data processing and analytical techniques enables central banks to monitor liquidity flows, calibrate money supply levels, and forecast economic behaviors more accurately. This study, employing a descriptive-analytical methodology and grounded in legal and economic sources, seeks to address a central question: To what extent can AI contribute to improving the processes of money creation and liquidity control within central banks, and what challenges and considerations are involved in its implementation? The findings suggested that strategic integration of AI into monetary policymaking—particularly in the domain of money creation—can lead to more informed decision-making, mitigation of financial risks, and increased policy effectiveness, thereby fostering greater public confidence in central banking institutions. Nevertheless, such integration necessitates adherence to specific prerequisites and regulatory frameworks, as the application of AI in the field of economics still requires consistent human oversight due to the limited specialized expertise at the intersection of economics and technology.

KEYWORDS

Artificial Intelligence (AI), Central Bank, Liquidity Management, Monetary Policy, Money Creation.

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Introduction

The transition to a digital economy over the past two decades has been one of the most significant transformations in the global economic landscape. This dynamic process goes beyond traditional methods and models of economic analysis, exerting rapid and wide-ranging impacts on economic structures and institutions. More precisely, financial and economic institutions in the contemporary era are undergoing continuous change, with innovations being implemented at an unprecedented pace. Like other sectors, the financial domain has also been deeply affected by digitalization. One of the major outcomes of this transformation is the dramatic increase in the volume of financial data, which has heightened the need for real-time and precise analytical capabilities. The analysis of such data—commonly referred to as "big data"—requires the deployment of tools such as AI and machine learning. These technologies have been proven to be effective in forecasting market behavior, assessing financial risks, and informing monetary policy decisions (Kahyaoğlu, 2021).

Amid the rapid transformations in economic structures and the evolving nature of financial systems, the integration of advanced technologies into the banking sector has become a fundamental necessity. Within this context, banks—as key components of the financial system—play a vital role in maintaining financial health and ensuring economic stability (Begenau & Landvoigt, 2015). In the new framework of the digital economy, the operations of central banks—recognized as the primary institutions of monetary governance—have also undergone significant changes. As the nature of monetary assets evolves, the central bank's traditional yet essential roles in areas such as money creation, liquidity management, and the execution of monetary policies now require redefinition. Traditional instruments are no longer sufficient for effectively monitoring and controlling circulating liquidity, particularly in a context where the continuous exchange of information among individuals, corporations, and institutions generates a constant flow of financial data. Consequently, the central bank's decision-making increasingly depends on real-time data analytics and predictive modeling.

In this context, AI is a branch of computer science that focuses on the design and implementation of systems capable of performing tasks that typically require human intelligence. These tasks include pattern recognition, situation prediction, natural language understanding, and effective interaction with the environment (Veloso et al., 2021). As one of the most groundbreaking technologies, AI has enabled machines to simulate human cognitive behaviors and capabilities with unprecedented accuracy, significantly expanding the boundaries of technological potential. This advancement has led some experts to regard AI as the driving force behind the "Fourth Industrial Revolution", as it fundamentally transforms production methods and information management by automating conventional industrial processes, analyzing complex data patterns, and fostering greater creativity and productivity (Njoroge, 2024).

One of the most critical challenges and key policy areas for central banks in preserving economic stability is the issue of money creation and liquidity control—two fundamental pillars of monetary policy. These components serve as essential instruments in the management of macroeconomic dynamics and consistently require timely and precise decision-making. In this context, using AI can serve as a novel tool for analyzing data and forecasting economic processes. Despite the wide-ranging capabilities of this technology, there remains a need for deeper examination of AI's capacities and limitations specifically in the domains of money creation and liquidity management. In other words, the application of AI in central bank monetary policy calls for a thorough assessment of the relevant conditions, opportunities, and challenges. The central research question addressed in this study is: How can AI play a significant role in improving the processes of money creation and liquidity control in central banks, and what considerations and challenges are associated with its implementation? Accordingly, the hypothesis underlying this research suggests that the integration of AI into the analysis and execution of monetary policies—particularly in the areas of money creation and liquidity control—can enhance the efficiency and predictability of these policies within central banks. However, its implementation is confronted by challenges related to model accuracy, data availability, and technological acceptance.

To achieve the research objectives and address the central question, the study begins with a review of the theoretical foundations and literature, including the conceptual framework, background, and research methodology. This is followed by an evaluation of the redesign of money creation and liquidity control through the application of AI, structured around defined principles. The final section of the paper is devoted to assessing the effectiveness and risk-related considerations of AI in the formulation of monetary policy.

Theoretical Foundations and Literature Review

This section first outlines the theoretical and conceptual framework of the study, followed by an examination of the research background and methodology.

Theoretical and Conceptual Framework

Analyzing the role of AI in controlling liquidity and implementing the monetary policies of central bank—particularly in the domain of money creation—requires a clear understanding of the key concepts in this field. Terms such as "money creation", "liquidity", and "liquidity management", each hold a distinct position within the framework of monetary policy and central bank regulation. Accordingly, in this the concept of oversight is defined first, followed by an in-depth examination of liquidity and its management, in order to pave the way for further discussions.

1. Money Creation

Money creation—or credit creation—is a process through which a country's money supply expands, resulting in generation of new credit in addition to the existing one (Akbari et al., 2020). There are two main types of money creation: exogenous (external) and endogenous (internal). Exogenous money creation refers to the issuance of highpowered money by the central bank, which can take various forms such as lending to commercial banks, purchasing government securities from them, providing credit to the government, or altering the bank's foreign asset holdings. Endogenous money creation, on the other hand, occurs through the processes of deposit-taking and credit issuance by commercial banks within the framework of fractional reserve banking or through changes in the required reserve ratio (Arabi & Meysami, 2019). From certain perspectives, money creation is considered as one of the most important innovations of humanity and the central function of modern banks. Some even regard it as the “miracle” of contemporary banking (Arabi & Meysami, 2019).

Throughout the money creation process, various agents and decision-makers interact and influence the outcomes. The central bank, commercial banks, and the public are considered the primary stakeholders in this process. Some scholars (e.g., Jafarzadeh & Akbarifard, 2013) identify the central bank as the most influential actor, followed by commercial banks. According to their view, the central bank plays a pivotal role in money creation by issuing banknotes, providing credit and loans to commercial banks, and enforcing regulatory frameworks that govern commercial banking activities. Commercial banks contribute to this process by accepting deposits from customers and extending loans based on those deposits. Meanwhile, the public participates by making decisions regarding how to hold money—whether in the form of cash or bank deposits—thus enabling commercial banks to issue loans. These interactions collectively shape the mechanism of money creation.

In contrast, some scholars argue that, in coordination with the central bank, the majority of money in a modern economy is created by commercial banks that extend loans (McLeay et al., 2014). These banks are, in fact, responsible for creating most of the new money through lending (Ingham et al., 2016). Others view the money creation process as a dual-entry accounting process. According to this perspective, when the central bank prints new banknotes and circulates them within the banking network, the newly issued currency is considered as a claim on the central bank and is recorded as a liability on the central bank's balance sheet. To maintain the balance in the central bank's balance sheet, new liabilities must be backed by new assets. In modern times, to support the issuance of banknotes or liabilities on its balance sheet, the central bank uses them to purchase new assets such as government securities (e.g., treasury bills or domestic bonds), foreign currencies, foreign government securities, or even gold (Moenjak, 2021). Next, we will discuss the meaning of liquidity and its management.

2. Liquidity and Liquidity Management

Liquidity refers to a government's ability to meet its matured financial obligations. This capacity depends on the availability of financial resources and the speed at which they can be converted into cash to cover short-term debts. If the government's financial management can fulfill its liabilities on time without incurring additional costs or imposing financial stress, it is considered to possess sufficient liquidity. A decline in liquidity levels may expose the financial system to crises or hinder its ability to repay obligations (Kolb, 1983). Some define liquidity as the pool of capital readily available to swiftly finance operations and meet obligations to creditors. Today, a significant portion of this capital circulates in the form of credit rather than physical cash. In financial institutions, liquidity is strictly defined as the ability to maintain sufficient financial resources to meet their maturing obligations. This includes complying with reserve requirements, facilitating interbank payments and financial settlements, managing cash flows, and covering other withdrawal-related liabilities.

Maintaining a certain level of cash to address emergencies and seize financial opportunities is associated with the concept of liquidity in economic literature (Bierman & Hass, 1963). Since individuals' bank balances in accounts' savings and time deposits can quickly be converted into purchasing power, the total of these funds is economically referred to as "quasi-money". Accordingly, liquidity refers to the total sum of money and quasi-money, which is commonly represented by the symbol M2 in economic resources. From the perspective of the European Central Bank, despite the widespread use of the term liquidity in financial and economic contexts, establishing a single, precise definition remains challenging. Economic theory offers at least two distinct interpretations of liquidity. The first is monetary liquidity, which is related to the amount of cash assets in the economy and is closely tied to levels of interest rate. The second is market liquidity, which measures the ability of market participants to conduct secure transactions without causing significant price fluctuations (European Central Bank, 2007).

Liquidity management is currently considered as one of the most important duties of central banks worldwide, encompassing the primary policy objectives of these banks. Through conducting this responsibility, other functions of the central bank are carried out, and its goals in liquidity management are achieved (Hashemi Dizaj, 2010). According to the regulations of the Bank for International Settlements, often referred to as the central bank of central banks, it is stated that: "A central bank is one that has the responsibility of regulating credit and controlling the volume of money in circulation". According to the International Encyclopedia of Finance and Banking, "central banks are government institutions that have legal authority over the issuance of national currency and the control of its supply" (Shim & Kontas, 2009).

Given the growing importance of liquidity and money creation in achieving the macroeconomic objectives, exploring the mechanisms that affect these two areas has always been a central focus for economists and monetary policymakers. Classical and neoclassical monetary theories primarily analyze money creation through the mechanism of bank lending and controlling interest rates by the central bank. In modern approaches, the role of expectations, the structure of financial markets, and even behavioral interactions have also been examined in explaining how liquidity is managed and how monetary policies affect the economy. In line with these discussions, it is clear that using new technologies, especially in data analysis, can lead to a deeper understanding of monetary behavior and identifying hidden patterns in liquidity fluctuations. The introduction of novel concepts such as data-driven approaches and machine learning models in contemporary economic literature reflects the reality that the analysis and implementation of monetary policies are no longer limited to traditional tools. This is especially true in environments where the complexity of markets, the speed of economic changes, and the changing behavior of economic agents have made policymakers in need of more precise and faster tools. Therefore, this research study aims to examine the integration of AI capabilities with monetary policy processes in light of the theoretical literature on liquidity, money creation, and the role of central banks in these areas. This effort primarily seeks to bridge classical foundations with emerging capacities and assess their alignment with the needs of modern monetary policy in today's economic environment. Following this, a brief review of the research literature will be provided.

Literature Review

In recent years, research related to the application of AI in financial systems, macroeconomic data analysis, economic indicator forecasting, and even financial regulation has been on the rise. These studies have shown that under certain conditions, modern technologies can play a significant role in economic decision-making.

Efuntade and Efuntade (2024) examined the application of AI in liquidity management within Nigeria's financial system and showed that AI can play a key role in optimizing resource allocation, predicting liquidity needs, and enhancing monetary stability. The author, utilizing discourse analysis, identified the advantages, challenges, and implementation requirements of AI. Key factors for successful implementation included data infrastructure, collaboration with technology companies, establishment of legal frameworks, and human resource training. Additionally, the importance of launching pilot projects and leveraging international experiences in the process of integrating AI into monetary policy was emphasized in the results. Njoroge (2024), Director of the monetary institution COMESAK, explored various aspects of AI implementation in monetary policymaking. He emphasized that key factors such as data quality, the selection of optimal algorithms, and ethical considerations play a crucial role in the success of this process.

According to his findings, AI should not be seen as a replacement for human resources in central banks, but rather as a complementary tool to enhance the quality of analysis, improve risk management, and increase efficiency in decision-making. Njoroge further identified the need for investment in data infrastructure, training of specialized human capital, and establishing robust oversight frameworks over the ethical and legal dimensions of the technology as essential prerequisites for effective AI deployment in liquidity management. In alignment with this perspective, Milana and Ashta (2021) also argued that the emergence of AI in financial sector has triggered a fundamental transformation. They believed that this technology can significantly contribute to improving efficiency, generating new types of data, and enhancing risk management, thereby playing a vital role in optimizing the performance of financial systems.

Ozili (2024) investigated the advantages and risks of using AI in central banks and indicated that AI can enhance the performance and efficiency of monetary policy by strengthening the central bank's capacity to analyze data, detect financial risks, and support macro- and micro-level data-driven policymaking. However, risks such as data privacy breaches, algorithmic biases, inaccurate outcomes, lack of transparency in AI-based decision-making, and cyber security threats have also been identified. In line with this view, Lin (2019) argued that despite the known applications of AI in financial systems, the cyber-security risks associated with its use remain significant. In another study in 2024, Ozili also explored the role of AI in the domain of central bank digital currencies (CBDCs) and its associated challenges. He emphasized that AI algorithms can assist central banks in improving efficiency, identifying risks, enhancing user services, combating financial crimes, and managing the supply and demand of digital currencies. Nevertheless, challenges such as privacy preservation, cyber-security concerns, and data bias persist. The author stressed that with responsible and ethics-oriented use of AI, alongside appropriate regulations, these challenges can be mitigated to pave the way for the sustainable development of CBDCs. Similar studies by Kahyaoğlu (2021), Qian (2019), and Lopez-Corleone et al. (2022) have also examined the use of AI and machine learning in improving performance, increasing security, and enhancing the efficiency of central banking tools, including digital currencies.

The review of the existing literature reveals that most of the referenced applications in previous studies are primarily related to areas such as risk management, digital currencies, market forecasting, and the associated challenges. However, there has been relatively little focused attention on the processes of monetary policymaking, particularly at the level of money creation instruments and liquidity management. This overlooked aspect in prior research highlights the need for a study that analytically explores the potential of leveraging AI in the realms of money creation and liquidity management, while also clarifying its effectiveness, challenges, and practical considerations.

Methodology

This study employs a descriptive-analytical approach, and the method of data collection is library-based. Given the novelty of the subject and the lack of comprehensive printed resources on the application of AI in monetary policy, the primary focus has been on the analysis of scholarly articles, reports published by specialized institutions in the field of money and banking, and credible electronic sources. These references offer the most recent perspectives and analyses regarding the role of AI in money creation and liquidity management, providing an up-to-date and analytical framework for examining the topic.

Findings

Redesigning Money Creation and Liquidity Management Using AI

Recent developments in digital technologies have opened new pathways for leveraging innovative tools in monetary policymaking process. Among these advancements, AI stands out as a key element, with the potential to significantly enhance the effectiveness of central bank decisions in two major domains of money creation and liquidity management. This section aims to extract and present the relevant content within a structured set of fundamental principles, in order to achieve more effective outcomes in redesigning money creation and liquidity management mechanisms under the influence of AI. Considering these principles helps bring coherence and organization to the analysis and provides a systematic framework for evaluating upcoming opportunities and challenges.

1. Transparency and Accountability

One of the most critical governance principles in redesigning money creation and liquidity control using AI is transparency and accountability, both of which are essential for maintaining public trust and the legitimacy of monetary institutions. The advanced algorithms currently employed to analyze cash flows, forecast monetary needs, or regulate money creation by commercial banks are highly complex. Decisions made through these systems can have wide-ranging implications for financial and monetary stability. In this context, it becomes imperative to clarify how these models operate, document their development and training phases, and precisely define the responsibilities associated with their outputs. These are unavoidable requirements of intelligent monetary governance.

For instance, when designing and deploying AI models to analyze interbank liquidity or make decisions on interest rates—one of the tools for liquidity control—it is crucial to maintain detailed records of model modifications, data sources used, validation mechanisms, and review procedures. This level of documentation ensures that the decision-making path remains fully traceable, thereby facilitating independent evaluations and internal audits. It also allows supervisory bodies to hold decision-makers accountable for potential deviations. Therefore, concepts like "human-in-the-loop", "human-on-the-loop", and "human-in-control"—which refer to active human involvement in the AI decision-making cycle—become even more significant in AI-driven monetary policymaking (Crisanto et al., 2024). In this context, the report published by the Bank of England on 21 November 2024 indicates that 84% of companies currently using AI identify assigning a responsible individual or team to oversee AI applications as the most common governance framework, control, or process they employ (Bank of England, 2024).

Moreover, in the realm of digital money creation or central bank digital currencies (CBDCs), transparency regarding allocation algorithms, transaction processing methods, and liquidity control approaches plays a crucial role in preventing public misperceptions, enhancing the legitimacy of the central bank, and increasing the effectiveness of monetary regulations. In other words, transparency in the performance of AI models provides a foundation for institutional accountability concerning decisions that may directly affect public access to money, inflation, or credit policies. Any use of AI in redesigning the mechanisms of money creation and liquidity control, without a clear regulatory framework and well-defined accountability, may lead to monetary instability or a decline in public trust (Deutsche Bundesbank, 2025). For this reason, many international organizations, including the European Central Bank and the Basel Committee, have emphasized the importance of algorithmic transparency, process documentation, and role of the human in key decision-making.

One of the major challenges associated with using AI, as suggested by some experts, is the absence of adequate legal and regulatory frameworks. Despite the potential risks posed by AI, there are minimal oversight mechanisms in place, and the existing laws often address AI only indirectly. AI has the capacity to empower a small group of individuals with the necessary expertise, and if these individuals harbor malicious intentions, they could exploit these powerful technologies to cause significant disruption (Shirzad & Rahmani, 2024). In this regard, the effective implementation of transparency and accountability requires the development of clear and binding legal and regulatory frameworks.

In the absence of such mechanisms, using complex and, in some cases, non-explainable models can pave the way for corruption, misuse of decision-making power, and the erosion of public trust. Therefore, forward-looking smart regulations must focus on three key pillars:

a. *Mandatory disclosure and documentation of algorithms and datasets*: Monetary authorities should be required to fully document and provide accessible versions of the algorithms, data sources used, and key decision-making parameters. Such transparency facilitates independent auditing and enables robust accountability mechanisms.

b. *Establishment of independent supervisory bodies with special authority in the AI domain*: To prevent excessive concentration of power within monetary institutions, specialized regulatory entities must oversee the development, deployment, and operation of AI-based models and be empowered to intervene effectively in case of errors or deviations.

c. *Formulation of ethical and legal principles governing the use of AI in monetary policymaking*: These principles should include provisions such as the prohibition of algorithmic discrimination, assurance of public access to relevant information, protection of privacy, and clear institutional responsibility for the social and economic consequences of algorithmic decisions.

2. Public Trust and Fairness Based on Oversight

In the process of utilizing AI in monetary policymaking—particularly in money creation and liquidity management—maintaining and strengthening public trust, upholding the principles of fairness, and ensuring human oversight in key decisions are fundamental requirements. Sole reliance on algorithms, without human supervisory mechanisms, may lead to systemic errors, unintended biases, or undermine the legitimacy of monetary policies. On one hand, money creation or the issuance of financial instruments such as participation bonds—when guided by AI-based models—must be backed by transparent human oversight and validation to prevent one-sided or unfair decisions imposed on the market. On the other hand, in the field of liquidity management, predictive analyses performed by AI should not replace human judgment, but rather serve as tools to enhance accuracy and enable timely responses. Especially in sensitive economic conditions, any decision made using AI models must be reviewed from social, ethical, and financial risk perspectives.

Achieving this principle requires transparency in AI decision-making processes, accountability of policymaking institutions regarding the outcomes of this technology, and consideration of distributive and procedural justice—ensuring that monetary policies are formulated with attention to the diverse economic and social conditions of different groups in society. More importantly, to prevent discrimination or injustice arising from algorithmic errors, systems must be designed to always allow for human review and final control. Machine-based decision-making, without accounting for human and societal dimensions, cannot fully meet the real needs of society. Economic and monetary decisions must always prioritize human insight and experience alongside machine analysis (Crisanto et al., 2024). More precisely, the increasing role of non-banking actors using AI technologies in the monetary and banking sectors has made the presence of experts—who possess up-to-date knowledge in both monetary economics and AI—an unavoidable necessity. This combination not only enhances the accuracy of economic analyses but also enables the alignment of decisions with social realities, public needs, and specific conditions through the contribution of informed human experts. This synergy between technology and human expertise adds greater depth to monetary policymaking and ensures its alignment with the actual conditions and economic requirements of society.

3. Technological Cooperation under a Responsible Legal Framework

In order to develop AI tools aligned with their operational requirements—particularly liquidity management—the Central Bank must be engaged in sustained collaborations with technology firms. These companies can play a pivotal role in designing and implementing AI-based systems (Ozili, 2020). At the initial stage, it would be prudent for the Central Bank to engage with smaller-scale projects, thereby enabling an empirical assessment of both the technology's capabilities and the competence of these firms. Such pilot initiatives may include AI-driven systems for forecasting liquidity needs or identifying associated risks. Moreover, monetary policy experts must establish clear ethical guidelines for the utilization of AI in liquidity management to ensure that the integration of such technologies occurs within a reliable framework (Efuntade & Efuntade, 2024). In this regard, designing a robust legal framework to govern the relationship between the Central Bank and AI service providers becomes indispensable. A desirable legal framework should, above all, guarantee the legal accountability of technology firms for the consequences arising from the operation of AI systems. In other words, the mere provision of technology must not be construed as exemption from responsibility or legal consequences. Furthermore, transparency in contractual terms and the processes of system development and deployment should be regarded as foundational pillars of any legal regulation. Obligations related to data use, analysis, and system performance must be clearly defined, such that the transfer of technology does not absolve providers from subsequent liabilities.

Strict requirements pertaining to data security and privacy must also be integrated into this framework—particularly in cases where sensitive financial data is made accessible to non-banking actors. Should AI systems malfunction or lead to data breaches, enforceable legal safeguards must be in place to protect both institutional and public interests. Therefore, clearly defined and enforceable remedies should be considered as integral components of the legal structure. Ongoing oversight mechanisms over both AI systems and their providers, as enacted by legislators and implemented by monetary authorities, are likewise essential. To this end, the Central Bank can draw upon the experiences of other countries and institutions that have previously undertaken similar initiatives. One of the most effective avenues for staying abreast of the latest developments in AI within monetary sectors is participation in international conferences and specialized forums on central banking and financial technology (Efuntade & Efuntade, 2024).

With the increasing penetration of Fintech[1] firms and major technology corporations into the credit market, the "AI-driven transformation" could gradually erode the traditional role of banks in financial intermediation. This shift could also reshape the transmission channels of monetary policy. Rather than being implemented solely through the banking system, policy effects may increasingly be transmitted via technologically adept non-bank institutions. For example, if investment funds leveraging AI are able to maintain more stable portfolios than banks, policies such as quantitative easing—which primarily target long-term interest rates—may influence money creation and liquidity through using entirely new mechanisms (Holm-Hadulla et al., 2023).

In such a context, the effectiveness of conventional tools of monetary policy may require reevaluation or supplementation with advanced technological instruments. Accordingly, the presence of flexible and forward-looking legal frameworks governing the relationships between monetary authorities and technology actors becomes not only beneficial but indispensable.

Measuring Efficiency and Assessing Risks of Utilizing AI in Monetary Policy

As mentioned in the previous section, the introduction of AI into the field of monetary policy has created new opportunities to improve decision-making in areas such as money creation, liquidity management, and the policies related to them. This technology, with its advanced processing capabilities and learning from vast datasets, can enhance the speed, accuracy, and flexibility of monetary policy responses to economic changes. However, the implementation of AI in the policymaking process comes with complexities and risks, requiring a detailed examination of its practical implications and associated risks in the monetary system. The technological potentials and opportunities of AI in the areas of money creation and liquidity management are explored in this section. Then, the

1. Financial technology.

operational risks and potential challenges of using this technology in monetary policy formulation are discussed.

1. Technological Opportunities of AI in Money Creation and Liquidity Control

Although AI has been used for several years by central banks to analyze market trends and optimize financial services, its current role has significantly expanded. AI now plays a deeper part in decision-making processes by conducting complex data analyses, uncovering hidden patterns, predicting economic developments, and even offering initial interpretations. This shift largely stems from the growing trust in AI technologies — a trust that views AI as more accurate, impartial, and less vulnerable to human error. In such a context, employing AI in monetary policy design presents a valuable opportunity to enhance the efficiency and improve the speed of response to economic changes (Chakraborty & Joseph, 2017). On the other hand, the application of AI can enable more precise supervision of the banking system. Through conducting advanced financial data analysis and high-volume data processing, central banks will be able to identify potential systemic banking risks and prevent financial crises. More specifically, AI allows central banks to detect financial problems before they materialize them by conducting more detailed analyses of macro- and micro-level data, enabling timely preventive and corrective measures.

Moreover, by leveraging AI capabilities, central banks can simulate and forecast subtle and timely fluctuations in money supply within the economy. This enhances the efficiency of adjusting and aligning various monetary policies such as interest rates and open market operations. In this regard, AI equips central banks with the means to more precisely analyze the behavior of commercial banks and financial institutions, monitor their performance, and assess the impact of their actions on overall banking system liquidity. Consequently, central banks will be able to make more accurate and timely supervisory decisions to effectively manage liquidity (Njoroge, 2024).

International organizations specializing in monetary and banking affairs—such as the International Monetary Fund (IMF), the Bank for International Settlements (BIS), and the Basel Committee—can play a key role in enhancing the use of emerging technologies in the monetary domain, thanks to their deep understanding of global financial dynamics and access to accurate and up-to-date knowledge and data. These institutions can support countries by transferring expertise in advanced analytics, big data, and AI algorithms, thereby enabling more precise design and implementation of monetary policies, particularly in liquidity management and money creation. In this context, these organizations—especially the Basel Committee—possess practical achievements in developing policies and supervisory recommendations that can assist developing countries in improving their monetary policy frameworks and liquidity control. Moreover, they can take effective steps in optimizing the use of AI and new technologies in monetary policymaking by offering training and capacity building for central banks on one hand, and developing legal frameworks and enforcement mechanisms on the other.

Some experts believe that using AI systems to analyze financial data can help central banks enhance the effectiveness of monetary policy. By leveraging the power of advanced processing and pattern recognition, these systems can proactively identify abnormal changes in the performance data of financial institutions and reveal early warning signs of potential stress in the money market (Ozili, 2024). This level of advanced analysis allows central banks to respond more timely and accurately to changes in liquidity conditions, thereby improving financial stability through timely intervention, better regulation of money flows in the economy, and avoiding confusion in the face of liquidity fluctuations. In this regard, AI plays a key role in transforming monetary policy from a reactive approach to a more forward-looking and stable one. In short, central banks can utilize AI technologies to promptly detect any abnormal changes in financial data reported by institutions, which may indicate vulnerabilities or deterioration in the condition of one or more entities within the banking system. This enables the central bank to assess these changes in a timely manner and intervene within the financial network before such risks evolve into systemic threats.

Central banks can also utilize AI to extract micro-level economic and non-economic data from various online sources such as news websites, social media platforms, and other digital environments. These data, often generated by the public and businesses in the virtual space, can offer valuable insights into trends in the money and capital markets, public expectations, and economic behavior (Shabsigh & Boukherouaa, 2023). Despite the high potential of such information, many central banks are either unaware of these sources or remain hesitant to use them in monetary and economic policy-making due to their unstructured nature and third-party origins. However, the intelligent and systematic use of this data can significantly enhance the policy-making process, improve understanding of household and business needs, and allow for more accurate calibration of policy tools, including liquidity management.

Although AI is widely regarded by experts as having substantial potential to improve the quality of monetary policy, it is also accompanied by considerable operational and institutional challenges. In the following section, some of the most important challenges are highlighted.

2. Operational Challenges in Utilizing AI for Monetary Policies

Given the rapid advancements in AI and its diverse applications, one of the primary concerns—explicitly or implicitly mentioned by most scholars in related literature—is using AI to create false or manipulated content (Njoroge, 2024). These alterations may appear in the form of images, videos, audio recordings, or other digital data. One of the most serious threats in this area is the generation and dissemination of fake content involving prominent figures in economic and financial sectors, especially those with central roles in monetary policy-making. AI has the capability to reconstruct digital content with such precision and speed that the resulting material appears convincingly real. In sensitive areas like financial and monetary systems, this phenomenon can mislead public opinion, trigger social and economic crises, and undermine trust in key institutions such as central banks. Techniques like “deep fakes”, which simulate the voice, appearance, or video of high-profile economic personalities, can be exploited by malicious actors to manipulate economic decisions and perceptions. Considering the growing prevalence of AI, there is a critical need to establish strict legal frameworks and transparent technologies to detect and counter manipulated and fake content. Such measures are essential to safeguard monetary systems, maintain public confidence, and prevent the undue influence of manipulated information on governmental and financial institutions.

Another significant concern in the context of risks associated with AI applications in monetary policy is the phenomenon known as “AI hallucination”. This occurs when intelligent systems, due to biased datasets or flawed algorithm design, produce incorrect and misleading outputs—even when the input data is valid and accurate. Since AI algorithms are often designed to simulate human decision-making processes, their erroneous outputs may not be easily identifiable as false. This issue is particularly critical in the financial policy domain, where central banks and monetary authorities rely on such systems for macroeconomic assessments. If AI-based tools deliver inaccurate evaluations or unrealistic analyses of economic and financial conditions, they may lead to misguided policy decisions and deviations in monetary implementation strategies. Moreover, these systems are vulnerable to cyber threats that target financial infrastructures, including data breaches and model inversion attacks. In the latter case, attackers attempt to infer sensitive underlying information—such as model parameters or training data—by analyzing the outputs of intelligent systems (Angwin et al., 2016). The malicious manipulation or exposure of such data can result in identity spoofing of policymaking institutions or a general erosion of trust in official data and communications.

AI systems are particularly vulnerable during the data training phase, as malicious actors may inject corrupted or manipulated data into training sets, ultimately compromising the accuracy of algorithms and distorting the decision-making process (Shabsigh & Boukherouaa, 2023). Such tampering can result in inaccurate assessments of liquidity conditions or money creation trends, potentially triggering market anxiety, inflationary expectations, or even widespread bank runs caused by depositor panic. In this context, cyber security is not merely a technical issue but a fundamental necessity for effective monetary governance in the age of AI (Wirtz et al., 2020).

Effectively managing AI-generated content is a critical aspect of maintaining the credibility of monetary systems and ensuring financial stability in the digital age. Strategic investment in AI becomes imperative when such technologies possess the capability to generate deceptive content—such as fabricated images or simulated voice recordings—which may undermine public trust in core monetary institutions, especially central banks. Consequently, establishing specialized regulatory frameworks within the financial sector is an undeniable necessity. These frameworks should include technical requirements such as transparent labeling of AI-generated content, privacy protection, and prevention of algorithmic bias. Such regulations not only help mitigate systemic risks like fraud and money laundering but also enable central banks to implement monetary creation and liquidity management policies more effectively in an environment of sustained public trust. In this regard, some experts argue that responsible implementation of AI can bring about a positive transformation in monetary policymaking. If properly designed and monitored, AI systems can help prevent unintended biases while enhancing transparency in decision-making. Protecting the privacy of sensitive data and promoting fairness in distributional impacts of monetary policies are among the other benefits of responsible AI governance (Dignum, 2019). Given the inherent sensitivity of monetary policies and the central role of central banks in safeguarding economic stability, one of the primary challenges in deploying AI—aligned with this vision—is ensuring data confidentiality and privacy protection. AI models, especially during training and macroeconomic data analysis, require access to vast amounts of sensitive information. This raises serious concerns regarding data breaches, potential misuse, or even misinterpretation. Moreover, compliance with strict regulations such as the European Union's AI Act requires that all AI-based solutions be backed by comprehensive documentation, transparent mechanisms, and responsible data governance frameworks. Failure to do so may not only erode public confidence in monetary institutions but also amplify systemic risks arising from decisions based on unreliable data (Cipollone, 2024).

In a speech delivered on April 17, 2024, in Washington, D.C., Pablo Hernández de Cos—Chair of the Basel Committee on Banking Supervision and Governor of the Bank of Spain—highlighted a key challenge in deploying AI and machine learning models within monetary and financial systems. He noted that many foundational AI models are developed by a limited number of technology providers, leading to a form of institutional and technological dependency for banks (Hernández de Cos, 2024). This dependency, especially in the context of digital money creation or the calibration of novel monetary policy instruments, may exacerbate concentration risks and undermine monetary sovereignty.

Furthermore, the increasing reliance on cloud-based infrastructures and shared platforms could reduce the operational flexibility of central banks in managing crisis situations. In such a context, enhancing supervision of technology service providers and imposing stringent standards in governance, risk management, and operational resilience become essential to preserving the autonomy and effectiveness of monetary policy tools. Overreliance on third-party developed models may also reduce the banks' resilience to liquidity shocks and significantly heighten the concentration risk. These developments underscore the need for banks and regulatory authorities to not only leverage the benefits of the advanced technologies but also remain vigilant against the risks of excessive dependence on external algorithms and cloud platforms. To strengthen the adaptability of monetary systems and enhance the intelligent liquidity management, more robust precautionary frameworks must be established.

Another significant challenge in utilizing AI in monetary policymaking is the issue of goal misalignment. This challenge arises when AI adheres to the objectives set by human decision-makers. When intelligent systems are faced with a set of multiple and sometimes conflicting goals, such as profit maximization, ethical compliance, and avoiding legal violations, the prioritization of these goals may be carried out in an unintended and undesirable manner. This issue becomes especially pronounced when abstract motivations or missions are assigned to AI, while it encounters situations that are not present in the training data. In the financial domain, this situation can lead to serious consequences, including the exacerbation of destabilizing behaviors during financial crises. For example, when financial institutions face liquidity pressures and seek immediate survival, their simultaneous actions may lead to phenomena such as forced asset sales, capital flight, or credit shortages in the market. These misalignments can become even more complex when several AI systems are interacting, learning, and reacting at the same time. Such systems might inadvertently exploit common mechanisms in financial markets, such as strategic complements, to shape behaviors like market manipulation or the creation of quasi-cartel structures. Given that AI has a high capacity to evade oversight, early detection of these behaviors also becomes a significant challenge (Danielsson & Uthemann, 2024). In this regard, it is evident that the best decision proposed by AI tools may not align with the interests or mission of the financial institution. While such incorrect or inconsistent behaviors are also common in human systems, as financial systems increasingly rely on AI, the likelihood of these behaviors occurring and recurring will also rise. The opportunities and challenges of applying AI in monetary policy-making are summarized in Table 1.

Table 1.
Opportunities and Challenges of Using AI in Monetary Policy

Row	Opportunities	Challenges
1	Enhancing the efficiency and speed of response to economic developments.	Risk of generating inaccurate outcomes due to data and algorithmic biases.
2	AI can provide more complex analyses of financial data and enable faster reactions to economic fluctuations.	AI may lead to systematic errors that are difficult to correct.
3	More accurate forecasting of economic developments and better adjustment of monetary policies.	Vulnerability to cyber-attacks: AI systems may be targeted, threatening the security of data and decisions made by monetary bodies.
4	By simulating changes in the money supply and their economic impacts, central banks can make more timely and accurate decisions.	Risk of data manipulation: Hackers may alter sensitive data or liquidity information, potentially causing financial unrest or crises.
5	Increasing transparency in monetary policymaking.	Decline in public trust due to the spread of misinformation: Incorrect decisions may reduce confidence in monetary institutions.
6	AI can make decision-making processes more transparent and reduce human biases.	Vulnerability during data training: Inserting corrupted data into datasets can decrease the accuracy of algorithms.
7	Ability to simulate the behavior of commercial banks and financial institutions.	High costs for implementation and maintenance: AI requires advanced infrastructure and entails substantial operational expenses.
8	As AI can analyze data from banks and financial institutions, it can help optimize liquidity supervision.	Detecting and correcting inaccurate AI-generated data can be complex and time-consuming.
9	—	Increased dependency on third-party service providers: Over-reliance on foundational models developed by a few companies.
10	—	Misalignment between the goals of human decision-makers and AI.

(Source: Researcher's Findings)

Discussion and Conclusion

Using AI in monetary policy and liquidity management, while offering a novel opportunity to enhance efficiency and precision in decision-making, requires a careful, structured approach due to the sensitivity and complexity of this field. One of the key challenges in this regard is the lack of a unified, international definition for AI in financial and monetary spheres. This absence of global standards can lead to a lack of coordination in the implementation of this technology across different countries, resulting in unpredictable problems in decision-making processes and execution of monetary policies. Furthermore, the effective use of AI in this area necessitates the involvement of human experts who simultaneously possess expertise in economics, monetary policy, and technology. Without such expertise, the application of AI in monetary policies may lead to incorrect or even harmful decisions. Therefore, combining AI with human oversight, especially in areas such as money creation and liquidity control, is an unavoidable necessity. AI must serve as a supportive tool alongside economic decision-makers, and should not automatically replace human judgment.

In addition, using AI in monetary and financial policies requires clear governance frameworks and ethical obligations. Without continuous oversight and establishment of clear international laws and regulations, the use of this technology could result in negative consequences, including financial crises. In this regard, institutions such as the Bank for International Settlements (BIS) and the Basel Committee play a crucial role in formulating global regulations and standards. These institutions should ensure that countries can effectively and safely employ AI in their monetary policies by adhering to these standards and regulations.

Ultimately, to effectively harness the potential of AI in money creation and liquidity control, a balance must be struck between technological innovation and legal, ethical, and human responsibilities. In other words, AI can serve to improve monetary operations, provided that it is employed within appropriate frameworks and under precise human oversight, continuously subject to evaluation and improvement. Such an approach can contribute to the creation of a more efficient, transparent, and resilient monetary system capable of withstanding crises.

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Investigating the Impact of Threat-Oriented Interpretation in Climate Changes on Innovation: the Mediator Role of Innovation Capacity in Focus

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ABSTRACT

One of the dire concequences of innovation is rapid reaction to developments and changes in the environment, and this depends on the managers' ability to reflect on the changes in the environment and various aspects of business. The aim of this study is to investigate the effect of threat-oriented interpretation in climate changes on innovation and its dimensions (behavioral innovation, product innovation, process innovation, market innovation, and strategic innovation). Statistical population of this research consists of executives who belong to chemical and petroleum industries listed on the stock exchange. The data was collected using questionnaires from 79 companies. Structured Equation Modeling (SEM) and Partial Least Squares (PLS) methods were employedto analyze the data. The results showed that the threat-oriented interpretation in climate change has no direct effect on innovation. However, it indirectly and negatively affects innovation. The innovation capacity generally mediates this relationship.

KEYWORDS

Climate Changes, Innovation and Innovation Capacity, Threat Oriented Interpretation.

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Introduction

Climate change presents one of the most significant environmental challenges that organizations face today, requiring innovative responses to ensure adaptation and sustainability. How managers interpret these environmental challenges—as either threats or opportunities—can significantly influence their strategic decisions and innovation outcomes (Cristofaro, 2020; Pitelis & Wagner, 2019). The cognitive processes through which managers interpret climate change challenges represent a critical dimension of their dynamic capabilities, with direct implications for organizational innovation and adaptation (Greve & Teh, 2022; Shepherd et al., 2019).

Research has established that threat-oriented interpretations of environmental changes can trigger specific cognitive and behavioral responses in managers. When perceiving threats, managers often experience heightened anxiety and psychological stress that can constrain their decision-making processes, leading them to rely on familiar information-seeking patterns rather than exploring innovative approaches (Ocasio et al., 2018). This cognitive constraint becomes particularly significant in the context of climate change, where novel perspectives and innovative solutions are essential. Recent studies by Talafidaryani and Asarian (2023) emphasize how managerial interpretations shape organizational responses to environmental disruptions across industries. Similarly, Hafezniya and Ansari (2024), in their systematic literature review, highlight that specific cognitive capabilities are crucial for effective decision-making in turbulent environmental contexts. These perspectives directly inform our study's examination of how managers' interpretations of climate change challenges influence their innovation capacity and innovation outcomes.

Despite these advances in understanding managerial cognition in environmental contexts, a critical gap remains in understanding how threat-oriented interpretations specifically mediate innovation outcomes through organizational capabilities—a gap our study addresses by examining the mediating role of innovation capacity.

Research indicates that, alongside factors like R&D intensity (Cui et al., 2018), organizational size, institutional capacity, and learning (Chege et al., 2020), absorptive capacity and combined capabilities (Yazdani et al., 2021), managers' cognitive processes are critical for innovation (Lee & Trimi, 2021). Managers' dynamic capabilities—identifying external challenges—enable organizational flexibility in building and reconfiguring capabilities (Schoemaker et al., 2018). These capabilities can be assessed at the managerial level (Akkaya & Tabak, 2020; Gölgeci et al., 2019). Perception and attention, as key cognitive traits, link to sensing opportunities and threats, with managerial interpretation shaping strategic change and innovation (Chang et al., 2021). Innovation capacity is essential for product, service, or process innovation (Yun et al., 2020) and drives creativity, entrepreneurship, and competition (Maier et al., 2020).

Climate change impacts businesses (Daddi et al., 2019), and the chemical industry must adhere to environmental regulations. It needs adaptive processes and innovative capabilities in products, processes, and strategies to thrive. This study explores how managers' perceptions of climate change influence innovative behavior in the chemical industry, focusing on the mediating role of innovation capacity.

Literature Review

Theoretical Foundations of Research

Interpretation of Managers

Interpretation refers to those cognitive activities and processes through which managers translate environmental data and stimuli into meaningful information that guides strategic action (Cristofaro, 2020). In the context of climate change, managerial interpretation plays a crucial role in determining organizational responses to environmental challenges. This interpretation process is grounded in categorization theory (Osiyevskyy et al., 2020; Shepherd et al., 2019), wherein managers classify environmental developments—such as climate change impacts—to reduce inherent complexity and guide decision-making (Joseph & Gaba, 2020). Recent experimental studies have shown that managers typically interpret climate-related developments through the lens of threats or opportunities (Kłopotek, 2020; Greve & Teh, 2022). These interpretations represent senior executives' beliefs about the potential impacts of climate change on their organizations (Pitelis & Wagner, 2019) and significantly influence strategic responses, including innovation initiatives (Daddi et al., 2019; Ocasio et al., 2018).

Innovation

Innovation is conceptualized as the capacity to respond to changes in the external environment and to impact and shape it (Lee & Trimi, 2021; Schoemaker et al., 2018). Innovation can manifest in various forms, such as product innovation, process innovation, radical or incremental innovation, and administrative or technological innovation (Cui et al., 2018; Yazdani et al., 2021). Scholars suggest a range of innovative options such as the development of new products or services, development of new methods of production, identification of new markets, exploration of new supply sources, and development of new organizational dimensions (Daddi et al., 2019). Recent research focuses on multiple dimensions: new product or service innovation, production methods or services, key executives' risk-taking, and search for unusual and innovative solutions (Chege et al., 2020). Table 1 briefly presents various aspects of innovation emphasized in different research studies.

Table 1.
Different Innovation Dimensions in Past Research Studies (Wang & Ahmed, 2004)

Author	Product innovation	Innovation in the market	Innovation in Process	Behavioral Innovation	Strategic Innovation
Lee & Trimi (2021)	✓	✓	✓		✓
Akkaya & Tabak (2020)	✓		✓	✓	
Chege et al. (2020)	✓	✓			✓
Yazdani et al. (2021)	✓		✓		

Author	Product innovation	Innovation in the market	Innovation in Process	Behavioral Innovation	Strategic Innovation
Cui et al. (2018)	✓	✓			
Daddi et al. (2019)		✓	✓		
Maier et al. (2020)	✓			✓	✓
Chang et al. (2021)	✓	✓	✓		
Yun et al. (2020)	✓	✓	✓	✓	✓

(Source: Researcher's Findings)

In line with these perspectives, innovation is defined as "the innovative ability of organizations to introduce new products to market or explore new markets through combining strategic orientation with behavior and innovative processes". According to Gölgeci et al. (2019), innovation can be identified in five dimensions: behavioral innovation, product innovation, process innovation, market innovation, and strategic innovation.

Innovation Capacity

Innovation capacity is defined as the continuous improvement in organizational features and capabilities that enable a company to discover and take advantage of opportunities to develop new products meeting market needs (Yun et al., 2020). Three different approaches are provided by researchers for measuring organizational innovation capacity (Maier et al., 2020).

In the first approach, the number of patents serves as a benchmark to measure innovation output (Piening & Salge, 2022), though this is considered an inadequate indicator in evaluating innovative performance, as patents are not the only way to protect knowledge and technology, and many firms are reluctant to patent (Prajogo, 2020).

In the second approach, researchers use resources allocated to innovation as the basis for measurement (Nylund et al., 2019). These resources include human resources (number of researchers and designers working on innovation projects), financial resources (funds dedicated to investments in new products and R&D), and physical assets (laboratory equipment and computer design systems) (Kahn et al., 2022).

Finally, the third approach examines innovation ability in physical facilities, skills, knowledge, and both tangible and intangible assets available to organizations in processes related to innovation and innovation management. This approach focuses on the process itself (Iddris, 2019). Moreover, the integration of Industry 4.0 technologies, such as IoT and big data analytics, can enhance innovation capacity by enabling sustainable processes and efficient resource utilization (Zarei & Naderi, 2024).

Development of Research Hypotheses and Conceptual Model

Interpretation of Managers and Innovation

Research in the management cognitive field argues that the manager's interpretation of situations or specific requirements significantly impacts the actions taken and is associated with changes in environmental strategies (Hahn et al., 2014). Negative assessment of issues can lead to psychological stress and anxiety among managers, affecting their decision-making capabilities (Chengyuan et al., 2016). The effects of negative evaluations on decision-making processes are well documented, indicating that when decision-makers encounter problems they perceive as threatening, they tend to seek less information or only information that is familiar (Mitchell et al., 2021). Under these conditions, senior managers are likely to rely on traditional search mechanisms established within their current organizational structures. Consequently, new and innovative information fails to emerge, as the interpretative frameworks of managers do not align with these innovations (Chengyuan et al., 2016). Henny Brophy, in evaluating the impacts of managers' interpretations of environmental changes on innovation in products and services concluded that as a manager's interpretation of environmental changes becomes threat-based, innovative responses significantly decrease (Wen & Zhu, 2019). Similarly, research has highlighted that a threat-based interpretation regarding environmental changes adversely affects innovation in both product and process dimensions (Todd et al., 2016). Additionally, investigations conducted by Vos et al. indicated that negative evaluations of events have a detrimental impact on the innovative behavior of companies (Liu et al., 2019). Thus, it can be posited that the managers' threat-based interpretations regarding environmental changes negatively impact innovation across multiple dimensions, including behavioral innovation, product innovation, process innovation, market innovation, and strategic innovation (Hahn et al., 2014).

Interpretation of Managers and Innovation Capacity

The capacity for innovation is defined as the continuous improvement of an organization's capabilities to create opportunities for product innovation and manufacturing processes. The foundational work by Lawrence and Lorsch (1967) on organizational responses to the environment, along with the opportunity framework introduced by Learned et al. (1965), spurred research on organizational capabilities and cognitive management features (Grewatsch & Kleindienst, 2018). The resource-based view addresses varying performance outcomes among organizations within the same environment, highlighting that differences arise from the varying capabilities in leveraging similar resources, irrespective of managers' interpretations of their activities' results (Khosravi et al., 2023; Santoso et al., 2022). Conversely, cognitive management scholars argue that managers' interpretations of their environments substantially influence the quality of organizational responses (Dabić et al., 2020; Martins et al., 2015). In this context, Eggers and Kaplan (2009) reconcile these perspectives by illustrating that a misalignment between capabilities and market conditions occurs when managers' beliefs about opportunities diverge from reality (Kurniati et al., 2019). Furthermore, capabilities related to resource allocation have significant implications for innovation capacity (Helfat & Peteraf, 2014). Kaplan and Henderson (2005) assert that these capabilities stem from the concepts and interpretations managers hold regarding their operational processes (Riana et al., 2023). Danneels (2011) highlights that managerial interpretations shape the nature and efficacy of procedures and capabilities over time (Pryor et al., 2015). Managers often resort to traditional search mechanisms when interpreting events as threats, which can inhibit the pursuit of complex and nuanced information (Li et al., 2018). Consequently, threat-based interpretations can impede the effective utilization of organizational capabilities, particularly affecting innovation capacity (Bingham & Haleblian, 2012).

The Impact of Innovation Capacity on Innovation

Innovation relies on an infrastructure that can be broadly divided into two categories: potential and actual. The potential dimension, known as "innovation capacity," reflects on an organization's latent ability to innovate, while the actual dimension, termed "innovation capability," represents its realized outcomes (Morais et al., 2022). Li and Xing (2017) define innovation capacity as a firm's potential to undertake innovation activities, such as developing new products, services, processes, and ideas. This capacity hinges on an organization's inherent resources and capabilities, which are critical drivers of innovation (Dias et al., 2021). Piening and Salge (2015) argue that these capabilities are a key competitive advantage in dynamic industries, encompassing efforts like advancing internal and external research, acquiring external knowledge, and enhancing staff training—factors that bolster innovation in manufacturing processes (Sugar, 2024). Similarly, Senoubar et al. (2011) highlight that innovation stimulants, including knowledge management, innovation management, and IT management, significantly strengthen innovation capacity (Tang et al., 2020). Prajogo (2016) further posits that innovation capacity serves as a mediator, transforming these stimulants into tangible outcomes like product and process innovations (Shang & Hai-bing, 2024). In a similar vein, Asarian et al. (2025) demonstrate that strategic flexibility and proactive IT strategies enhance business performance, suggesting that such IT practices can amplify innovation capacity in dynamic environments.

Conceptual Model Research

Finally, in connection with what has been discussed in the previous section, the following research hypotheses were proposed. Conceptual model of research is shown in Figure 1.

First hypothesis (H1): The threat-based interpretation of managers from climate changes has a negative and significant effect on innovation.

This main hypothesis is further broken down into the following sub-hypotheses addressing each dimension of innovation:

H1-1: The threat-based interpretation of managers from climate changes has a negative and significant effect on behavioral innovation.

H1-2: The threat-based interpretation of managers from climate changes has a negative and significant effect on product innovation.

H1-3: The threat-based interpretation of managers from climate changes has a negative and significant effect on process innovation.

H1-4: The threat-based interpretation of managers from climate changes has a negative and significant effect on market innovation.

H1-5: The threat-based interpretation of managers from climate changes has a negative and significant effect on strategic innovation.

The second hypothesis: threat-based interpretation of managers from climate changes has a significant negative impact on innovation capacity.

Third hypothesis (H3): Innovation capacity has a positive and significant effect on innovation.

This main hypothesis is further broken down into the following sub-hypotheses addressing each dimension of innovation:

H3-1: Innovation capacity has a positive and significant effect on behavioral innovation.

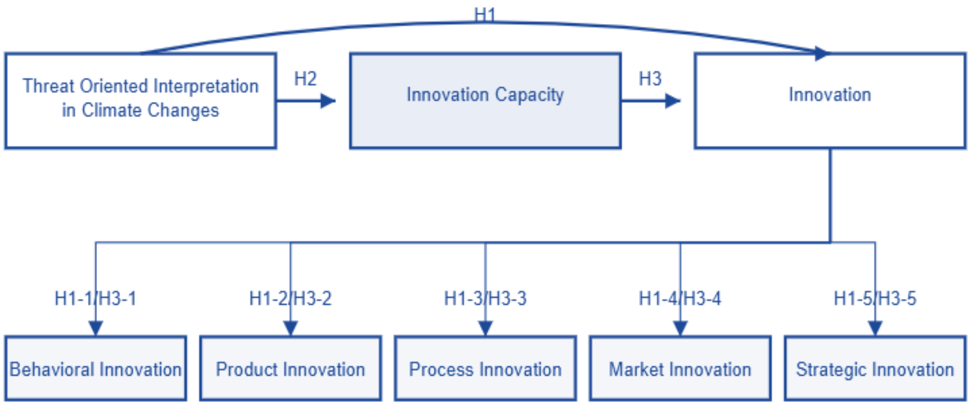
H3-2: Innovation capacity has a positive and significant effect on product innovation.

H3-3: Innovation capacity has a positive and significant effect on process innovation.

H3-4: Innovation capacity has a positive and significant effect on market innovation.

H3-5: Innovation capacity has a positive and significant effect on strategic innovation.

Figure 1.
Conceptual Model of Research



(Source: Researcher's Findings)

Methodology

Sample Selection and Access

This study employs an applied research approach, as it examines relationships between variables that can provide practical insights for organizational decision-makers. Our research design follows a descriptive-survey methodology, employing inferential statistical methods and structural equation modeling to test our hypotheses.

The research population consisted of companies in the chemical and petrochemical industries listed on the Tehran Stock Exchange. Based on official information from the Tehran Stock Exchange website, this population comprised 110 companies. Given that our research variables are quantitative and multi-valued with an ordinal scale, and the population size is limited, we calculated a sample size of 86 companies using the Cochran formula. This sampling approach ensured adequate statistical power while maintaining representativeness of the target population.

Data Collection Process

We collected data through questionnaires distributed to senior executives at the selected companies. The questionnaires were structured using a five-point Likert scale (1=complete disagreement to 5=complete agreement) for all measurement items. After distribution and follow-up, we received 79 completed questionnaires (representing a 91.9% response rate) that were used in the analysis stage. These respondents were senior managers with decision-making authority in their respective organizations, making them appropriate informants for assessing the variables under study.

The respondents in our study primarily held senior executive positions including CEOs (23%), operations directors (31%), and sustainability managers (46%). The mean industry experience of respondents was 12.7 years (SD = 4.3), with an average of 6.5 years (SD = 2.8) in their current role. All participants had direct involvement in strategic decision-making related to environmental initiatives and innovation processes within their organizations, making them appropriate informants for our research questions.

Questionnaire Validity and Reliability

We employed a rigorous process to ensure the validity and reliability of our measurement instrument. As detailed in our results section, we assessed construct validity through confirmatory factor analysis using SmartPLS software. As shown in Table 2, all measurement items except one (the fourth index of strategic innovation) achieved factor loadings above the recommended threshold of 0.4 (Hulland, 1999), leading us to remove that item from further analysis.

For reliability assessment, we utilized Cronbach's alpha coefficient. We initially distributed 30 questionnaires as a pretest and analyzed the resulting data to calculate alpha coefficients for each variable. As reported in the manuscript, all constructs demonstrated alpha values exceeding 0.7, confirming high reliability. In addition to Cronbach's alpha, we employed composite reliability as a complementary measure, which accounts for the relationship between constructs and their relative importance, rather than treating them as absolute values.

Data Analysis Techniques

Our data analysis employed structural equation modeling (SEM) with partial least squares (PLS) using SmartPLS software. The PLS-SEM approach was selected for its suitability for predictive research models and effectiveness with our sample size. Our analysis followed a systematic two-stage approach:

1. Assessment of the measurement model:
    - Evaluation of factorial loads (Table 2)
    - Analysis of reliability using Cronbach's alpha and composite reliability (Table 3)
    - Assessment of convergent validity using Average Variance Extracted (AVE) (Table 3)
    - Examination of discriminant validity using Fornell and Larcker criteria (Table 4)
2. Evaluation of the structural model:

- Analysis of path coefficients and t-statistics for hypothesis testing (Tables 6 and 7)
- Calculation of the coefficient of determination (R^2), with values categorized as weak (0.19), medium (0.33), or strong (0.67) following Chin (1998)
- Assessment of prediction power using the Q^2 coefficient, with values categorized as weak (0.02), medium (0.15), or strong (0.35) as suggested by Geisser (1975)
- Overall model fit evaluation using goodness-of-fit criteria, with our value of 0.468 exceeding the threshold for strong fit (0.36) as proposed by Wetzels et al. (2009)

This comprehensive analytical approach enabled us to rigorously test our hypotheses and evaluate the proposed relationships between threat-oriented interpretation, innovation capacity, and various dimensions of innovation.

Findings

In the data analysis, structural equation modeling with partial least squares method approach and SmartPLS software to evaluate research conceptual model were used. Following the findings of the study is investigated.

The Measurement Mode Assessment

Assessment of Factorial Loads of Measures

Factorial loads were calculated by calculating the correlation value of a structure indexes with that structure. Equal factorial loads or more than 0.4 indicates that variance between structure and its indexes is more than measurement error variance of that structure, and observable variable is reliable scale for hidden variable calculation (hulland, 1999). Obtained factorial loads from components of the model (shown in table 2) indicates that all measures except the fourth index of strategic innovation is more than 0.4 , so this index is deleted for the rest of analysis.

Table 2.
Factorial Load Coefficient

Variable	Row	Questions	Load factor
Behavioral Innovation (BIN)	1	We encourage people to think and behave in the new and novel ways.	553.0
	2	We compromise in participate with people who do things in a different way.	902.0
	3	We tend to try new ways of doing things and are looking for unusual and innovative solutions.	772.0
	4	We receive many support from the company to testing new new methods of doing things.	875.0
Innovation (PIN)	1	Our company compared to competitors, highly innovative products has introduced during the past 5 years.	842.0
	2	Our company to introduce new products and services to the market, is often the first.	788.0
	3	Our new products and services, is often perceived as innovative products and services by customers.	876.0
	4	Our company compared to competitors has a low success rate in delivering new products and services.	404.0
Innovation in process (PRIN)	1	We constantly improve upon their business processes.	804.0
	2	During the past five years, our company has developed new approaches to management.	597.0

Variable	Row	Questions	Load factor
	3	When we are unable to solve problems we devise new methods using traditional methods.	784.0
	4	Our company changes production of goods and services with great speed compared to competitors.	861.0
Innovation in the market (MIN)	1	A recent marketing program of our products compared to competitors in the market are very different.	850.0
	2	Our new products and services has minor changes compared to existing products and services on the market.	694.0
	3	Our company to introduce new products and services has often distinctive features in technology.	651.0
	4	New products and services of company, puts us in front of new competitors.	798.0
Strategic Innovation (SIN)	1	Our R & D department is responsible for the development of new products and services.	857.0
	2	Our company's key executives are willing to take risks to explore growth opportunities.	897.0
	3	Senior managers constantly are looking for unusual and innovative ways to solve problems.	723.0
	4	When we see the new ways doing things we adopt ourselves strictly with those methods.	288.0
Interpretation of managers from climate changes (MI)	1	Climate changes are negative consequences on our company's activities.	942.0
	2	Climate changes will lead to the loss of our company.	927.0
	3	Climate changes is causing the loss of new investment opportunities.	792.0
Knowledge Management (KNM)	1	The organization uses a variety of tools for acquiring knowledge.	955.0
	2	Members' knowledge of the organization is exchanged and transfer between each other.	856.0
	3	Organization in the creation and production of knowledge as well as is able to stabilize and protect it in organization.	947.0
	4	Organization assesses state of knowledge and their knowledge assets.	854.0
Creative Management (CM)	1	Organization collects the new ideas of suppliers systematically.	797.0
	2	Organization collects the new ideas of suppliers systematically.	927.0
	3	Organization collects the new ideas of suppliers systematically.	892.0
	4	Organization uses of the comments of suppliers and consumers during the designing process of new products.	868.0
Information Technology Management (ITM)	1	Organization uses the information technology (the market analysis tools) for the detection of market conditions.	873.0
	2	Organization uses information technology to create new processes and methods.	763.0
	3	Organization uses information technology to identify customers' needs.	953.0
	4	Organization uses the information technology to meet customer needs and servicing.	916.0
Human Resource Management (HRM)	1	Organization pays attention to develop and promote and product innovation in educational programs.	902.0
	2	Organization pays attention to ability to create ideas during recruiting.	772.0
	3	The organization pays attention to staff's commitment to product innovations in the design of incentive systems.	875.0
	4	The organization uses human resources specialized in the design of new products.	842.0
Communications (COM)	1	Senior managers use the systems, control methods and project Management.	788.0
	2	Technological, methodological and economic changes is tracking and following in the Organization.	876.0
	3	Organization cooperates with other firms to create participating networks.	404.0
	4	Organization allocates the necessary funds to design new products.	804.0

(Source: Researcher's Findings)

It should be noted that the reverse questions the value were gotten in calculating of their reversed value (for example, if answer of managers was 5, has been entered in the accounts 1, etc.)

Combining Reliability and Convergent Validity

Besides Cronbach's alpha, another criterion known as combining reliability offers distinct advantages to this method. The primary benefit of combining reliability over alpha is that it assesses the reliability of structures not only in an absolute sense but also by considering the interrelatedness of the structures themselves (Zhang & Duan, 2010).Convergent validity is another standard procedure for fitting the measurement models in structural equation modeling method. Fornell and Larkr (1981) suggested using from extracted variance average as a criterion for convergent validity and believed that convergent validity is established when the value of the extracted variance average for each construct is bigger than 0.5 (Davari & Rezazadeh, 2014). According to data from Table 3, the combining reliability of all research variables is higher than 0.7 and their extracted variance average all the variables of 7/0 is larger than 0.5. So the structures have sufficient reliability.

Table 3.
Report of Alpha Criteria, Combining Reliability and Convergent Validity

Latent variables	Title in model	(Alpha≥0.7)	(CR≥0.7)	(AVE≥0.5)
Behavioral Innovation	BIN	0.816	0.864	0.621
Product innovation	PIN	0.822	0.830	0.565
Innovation in Process	PRIN	0.850	0.864	0.589
Innovation in the market	MIN	0.839	0.838	0.566
Strategic Innovation	SIN	0.802	0.867	0.687
Interpretation managers	MI	0.865	0.919	0.792
knowledge management	KNM	0.925	0.947	0.818
Creative Management	CM	0.894	0.927	0.671
IT management	ITM	0.899	0.931	0.772
Human resources management	HRM	0.851	0.899	0.692
Process management and communication	COM	0.850	0.846	0.586

(Source: Researcher's Findings)

Divergent Validity

The criteria established by Fornell and Larcker are employed to evaluate the validity of the measurement model. According to this framework, the correlation of a construct with its respective indicators must exceed the correlation of that construct with other constructs. As indicated by the results presented in Table 4, the average squared value of the extracted variance for all constructs is greater than their correlation with other constructs in the model. Therefore, this study demonstrates that all constructs (latent variables) exhibit a stronger relationship with their own indicators than with other constructs, thereby establishing that the divergent validity of the model is satisfactory.

Table 4.
Correlation between Latent Variables and Values of AVE

Components	1	2	3	4	5	6	7	8	9	10	11
1. MI	0.89										
2. BIN	0.61	0.78									
3. PIN	0.27	0.12	0.75								
4. PRIN	-0.2	0.29	0.40	0.76							
5. MIN	0.46	0.71	0.27	0.44	0.75						
6. SIN	0.14	0.06	0.61	0.26	0.29	0.82					
7. KNM	0.29	0.31	0.75	0.58	0.44	0.58	0.90				
8. CM	0.48	0.59	0.75	0.56	0.51	0.37	0.74	0.87			
9. ITM	0.67	0.58	0.59	0.25	0.47	0.24	0.78	0.79	0.88		
10. HRM	0.55	0.52	0.66	0.39	0.54	0.69	0.82	0.74	0.74	0.83	
11. COM	0.66	0.74	0.48	0.40	0.75	0.41	0.70	0.76	0.73	0.68	0.76

(Source: Researcher's Findings)

The Structural Model assessment

Following the evaluation of the validity and reliability of the measurement, the structural model was assessed through the relationships among latent variables using three significant criteria: the t-value, the coefficient of determination (R2), and the prediction power factor (Q2).

The Coefficient of Determination and Prediction Power Coefficient

In order to evaluate the structural model through the criteria of the coefficient of determination as delineated by Chin (1998), values of 0.19, 0.33, and 0.67 have been established as benchmarks for weak, medium, and strong correlations, respectively. The results presented in Table 5 indicate that the latent variables exhibit a high level of correlation, implying a robust relationship among them. To assess the model's predictive capabilities, the predictive power coefficient, as introduced by Geisser (1975), was utilized. For endogenous structures demonstrating strong predictive power, the thresholds of 0.02, 0.15, and 0.35 were identified as indicators of weak, medium, and strong predictive values, respectively. The findings suggest that the model possesses a high degree of predictability.

Table 5.
Results of the Structural Fitting Model

Criterion Coefficient of determination (R2)	Innovation					Innovation capacity				
	BIN	PIN	PRIN	MIN	SIN	KNM	CM	ITM	HRM	COM
Power prediction Coefficient (Q2)	0.49	0.63	0.70	0.41	0.35	0.82	0.81	0.81	0.83	0.76
Criterion	0.29	0.35	0.40	0.22	0.16	0.67	0.61	0.61	0.55	0.42

(Source: Researcher's Findings)

Hypotheses tests

After evaluating of measurement fitting model and the structural model and fitting proper models, research hypotheses was studied and examined. Moreover, the results of meaningful coefficients for each of the hypotheses, the standard coefficients of related routes for each of the hypotheses in Tables (6) and (7) are provided.

Table 6.
Path Coefficients and Significant Values for Direct Effects

Hypotheses	Direction	Path coefficient	T statistic	Results
H_1	Threat oriented Interpretation →innovation	-0.184	-1.128	Hypothesis rejection
H_{1-1}	Threat oriented Interpretation →behavorial innovation	-0.470	-6.381	Confirmation of hypotheses
H_{1-2}	Threat oriented Interpretation → innovation in product	-0.279	-3.056	Confirmation of hypotheses
H_{1-3}	Threat oriented Interpretation → innovation in process	-0.789	-11.10	Confirmation of hypotheses
H_{1-4}	Threat oriented Interpretation → innovation in market	-0.281	-3.012	Confirmation of hypotheses
H_{1-5}	Threat oriented Interpretation → Strategic innovation	-0.247	-1.878	Hypothesis rejection
H_2	Threat oriented Interpretation → innovation capacity	-0.582	-6.616	Confirmation of hypotheses
H_3	innovation capacity→innovation	0.964	10.675	Confirmation of hypotheses
H_{3-1}	innovation capacity→ behavorial innovation	0.314	3.864	Confirmation of hypotheses
H_{3-2}	innovation capacity→ innovation in product	0.914	13.02	Confirmation of hypotheses
H_{3-3}	innovation capacity→ innovation in process	0.965	9.068	Confirmation of hypotheses
H_{3-4}	innovation capacity→ innovation in market	0.438	4.944	Confirmation of hypotheses
H_{3-5}	innovation capacity→ Strategic innovation	0.697	8.338	Confirmation of hypotheses

(Source: Researcher's Findings)

Table 7.
Path coefficients and significant values for direct effects

Direction	Path coefficient	T statistic	Results
Threat oriented Interpretation→ Innovation capacity→ Innovation	-0.560	-5.103	Confirmation of hypotheses
Threat oriented Interpretation→ Innovation capacity→ behavorial Innovation	-0.177	-2.657	Confirmation of hypotheses
Threat oriented Interpretation→ Innovation capacity→ Innovation in product	-0.515	-4.640	Confirmation of hypotheses
Threat oriented Interpretation→ Innovation capacity→ Innovation in process	-0.544	-3.625	Confirmation of hypotheses
Threat oriented Interpretation→ Innovation capacity→ Innovation in market	-0.248	-2.920	Confirmation of hypotheses
Threat oriented Interpretation→ Innovation capacity→ Strategic Innovation	-0.515	-3.847	Confirmation of hypotheses

(Source: Researcher's Findings)

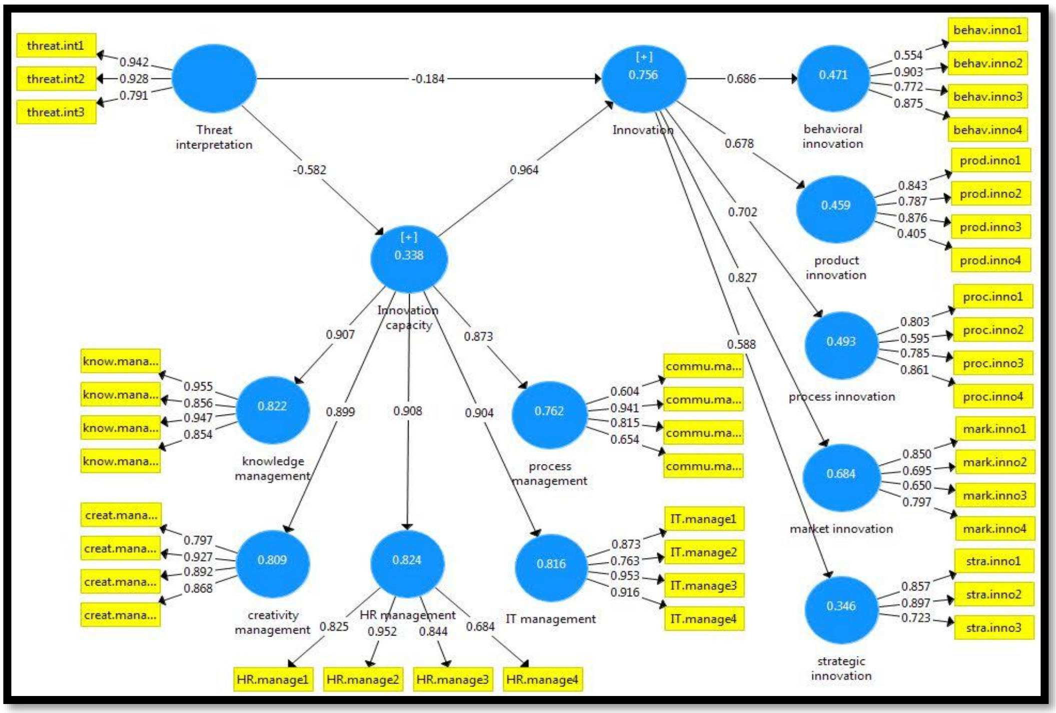
The results provide clear evidence regarding each of our hypotheses. For our first main hypothesis (H1), the path coefficient (-0.184) and t-statistic (-1.128) indicate that threat-oriented interpretation does not have a significant direct effect on overall innovation, leading to the rejection of H1. However, when examining the sub-hypotheses, we found significant negative effects on behavioral innovation (H1-1: path coefficient = -0.470, t = -6.381), product innovation (H1-2: path coefficient = -0.279, t = -3.056), process innovation (H1-3: path coefficient = -0.789, t = -11.10), and market innovation (H1-4: path coefficient = -0.281, t = -3.012). The effect on strategic innovation was not significant (H1-5: path coefficient = -0.247, t = -1.878), leading to the rejection of this sub-hypothesis.

For the second hypothesis (H2), our results strongly support that threat-oriented interpretation negatively affects innovation capacity (path coefficient = -0.582, t = -6.616).

For the third hypothesis (H3), we found strong support for the positive effect of innovation capacity on overall innovation (path coefficient = 0.964, t = 10.675). Each sub-hypothesis was also supported, with innovation capacity positively influencing behavioral innovation (H3-1: path coefficient = 0.314, t = 3.864), product innovation (H3-2: path coefficient = 0.914, t = 13.02), process innovation (H3-3: path coefficient = 0.965, t = 9.068), market innovation (H3-4: path coefficient = 0.438, t = 4.944), and strategic innovation (H3-5: path coefficient = 0.697, t = 8.338).

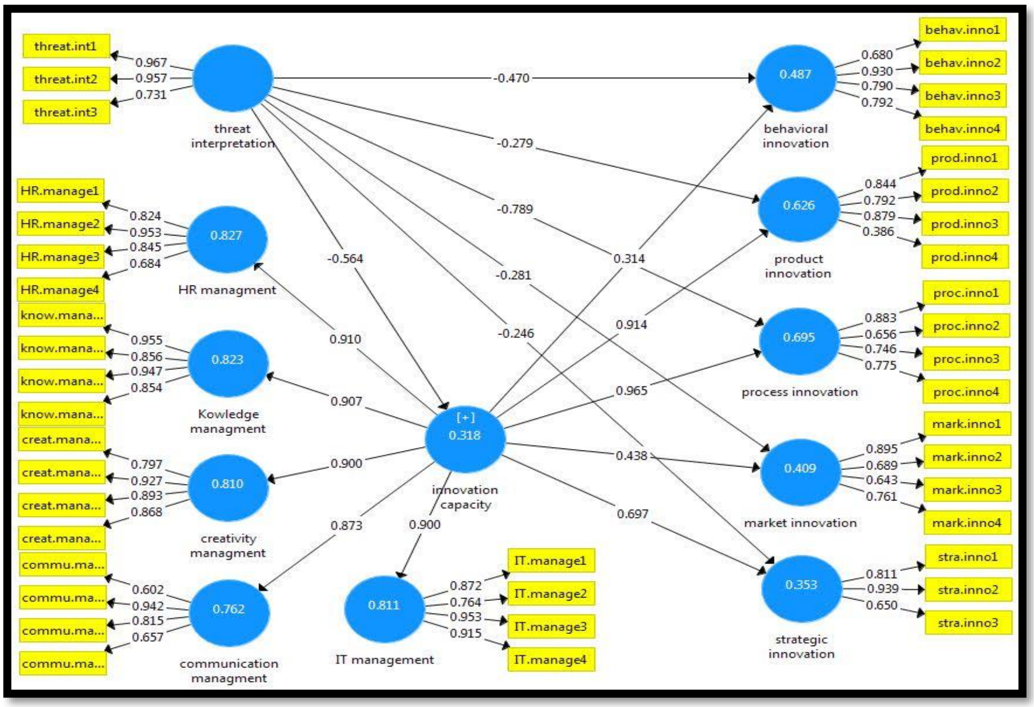
Furthermore, our mediation analysis (Table 7) confirms that innovation capacity mediates the relationship between threat-oriented interpretation and innovation dimensions, with significant indirect effects across all innovation components. Figure (2) and (3) are provided.

Figure 2.
Tested Model of Research (Path Coefficients and Factorial Loads)



(Source: Researcher's Findings)

Figure 3.
Tested Model of Research (Path Coefficient and Factorial Loads of Secondary Hypotheses)



(Source: Researcher's Findings)

The Overall Fit of the Model

Fitting goodness criteria is relegated to overall sector of structural equation modeling. This criterion allows for the regulation of the overall fitting sector subsequent to the measurement and structural fitting components. Wetzels et al (2009) have introduced three values 0.01, 0.25 and 0.36 values as weak, medium and strong values to this criteria (Wetzels et al., 2009). Considering that the mentioned value is 0.468, so overall fitting of model is confirmed as "strong".

Conclusion and Discussion

Discussion

This study examined the relationship between managers' threat-oriented interpretation of climate changes, innovation capacity, and innovation dimensions in chemical and petroleum industries. The findings reveal several important implications.

Our results show that threat-oriented interpretation of climate changes does not have a direct negative effect on overall innovation, contradicting the threat rigidity theory (Staw et al., 1981) and aligning with prospect theory (Kahneman & Tversky, 1979). However, our detailed analysis revealed that threat-oriented interpretation negatively affects behavioral innovation, product innovation, process innovation, and market innovation, while strategic innovation remains unaffected. This suggests that the relationship between threat perception and innovation is more complex than previously thought.

The confirmed negative relationship between threat-oriented interpretation and innovation capacity indicates that when managers view climate changes as threats, they tend to rely on traditional information search mechanisms rather than seeking novel information (Staw et al., 1981). This limits the organization's ability to effectively utilize its innovation capacity, supporting previous work by Eggers and Kaplan (2013) and Danneels (2011).

Our most significant finding is the mediating role of innovation capacity in the relationship between threat-oriented interpretation and innovation. This mediation effect reveals that managers' negative interpretations of climate changes impair innovation capacity, which in turn reduces innovative capabilities. This connects cognitive managerial processes to organizational outcomes through organizational capabilities.

For practitioners, these findings highlight the importance of developing cognitive capabilities that help overcome negative bias in interpreting environmental changes. Organizations may benefit from training programs that enhance managers' ability to see opportunities within threats, particularly regarding climate change.

Practical and Managerial Implications

Our findings offer important practical implications for organizations in industries affected by climate change. First, organizations should develop training programs to help managers recognize and overcome cognitive biases in environmental interpretation. These programs could include scenario planning exercises that challenge threat-based assumptions and encourage exploration of opportunities within environmental constraints.

Second, organizations should focus on strengthening innovation capacity components—knowledge management, innovation processes, IT capabilities, and cross-functional communication—as these can buffer against negative interpretations of climate change. Even when facing environmental threats, robust innovation capacity can maintain innovation momentum.

Third, companies should implement structured information-gathering systems that deliberately introduce diverse environmental perspectives, counteracting the tendency of managers under threat to seek only confirmed information. This could include establishing regular environmental scanning processes that consider both risks and opportunities.

By implementing these recommendations, organizations can create conditions that support innovation even when facing environmental challenges perceived as threatening, maintaining innovative momentum despite environmental pressures.

Conclusion

This study investigated the role of managers' cognitive variables in forming innovative acts, specifically examining how threat-based interpretation of climate changes affects innovation through innovation capacity. While previous research established that interpretation processes shape organizational responses (Ginsberg & Venkatraman, 1995), the mediating role of innovation capacity remained unexplored.

Our results show that threat-based interpretation does not directly affect overall innovation (t: -1.128), contradicting threat rigidity theory (Staw et al., 1981) but aligning with prospect theory (Kahneman & Tversky, 1979). However, detailed analysis revealed that threat-based interpretation negatively impacts behavioral innovation (t: -6.381), product innovation (t: -3.056), process innovation (t: -11.10), and market innovation (t: -3.012), while its effect on strategic innovation was not significant (t: -1.878).

Furthermore, threat-based interpretation negatively affects innovation capacity (t: -6.616), as managers facing threats rely on traditional information search mechanisms, limiting their ability to process new information (Staw et al., 1981). Innovation capacity positively influences all innovation dimensions (t: 10.675), consistent with findings from Senoubar et al. (2011) and Prajogo (2016).

Importantly, our study confirms the indirect negative effect of threat-based interpretation on innovation through innovation capacity (t: -5.103). This novel finding suggests that when managers interpret climate changes as threats, they restrict their organization's innovation capacity, which subsequently impairs innovation performance.

To overcome these challenges, organizations should enhance managers' decision-making skills and establish supportive decision-making structures. Future research should examine organizational factors such as information processing structure (Thomas & McDaniel, 1990), perceived control (Denison et al., 1996), and organizational climate (Hornsby et al., 2002) that influence managers' cognitive processes and entrepreneurial actions.

Limitations and Future Research Direction

This study has several limitations that provide opportunities for future research:

1. Cross-sectional Design: Our research employed a cross-sectional data collection approach, which limits our ability to establish definitive causal relationships between the variables.

Future Research: Longitudinal studies tracking how managers' interpretations of climate change evolve over time and their long-term effects on innovation capacity and outcomes would provide stronger causal evidence.

2. Industry Specificity: Our sample was drawn specifically from chemical and petroleum industries in the Iranian stock market, which may limit generalizability to other industries or contexts.

Future Research: Comparative studies across multiple industries and different national contexts would help establish the boundary conditions of our findings and enhance external validity.

3. Cognitive Biases: Our findings suggest that managers experiencing anxiety and psychological pressure from negative interpretations tend to gather information that only confirms their existing beliefs, falling into a confirmation bias trap.

Future Research: Studies incorporating experimental designs to investigate specific cognitive biases in environmental interpretation would deepen understanding of these psychological mechanisms.

4. Organizational Factors: This study focused primarily on managerial interpretations without extensively examining organizational moderators.

Future Research: Researchers should incorporate organizational factors such as information processing structure (Thomas & McDaniel, 1990), perceived control (Denison et al., 1996), and organizational climate (Hornsby et al., 2002) that might influence the relationship between managerial interpretation and innovation.

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Identifying the Effective Factors in Choosing Digital Currency Exchanges

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ABSTRACT

In a world where buying and selling digital currencies has become an integral part of the global economy, digital currency exchanges play a very important role. Therefore, the purpose of this article is to identify the effective factors in choosing digital currency exchanges. The present study is a qualitative research in terms of method, exploratory in terms of approach, applied in terms of purpose, interpretive in terms of data collection or the nature and method of the research. The statistical population of the research is the digital currency traders (inside Iran). Purposive sampling was used to select the participants, and 16 people were interviewed following the rule of theoretical saturation. The data collection tool is interview. Based on the findings of the research using the theme analysis method, six effective factors in choosing digital currency exchanges included security, liquidity, and volume of transactions, authentication, fees, support, and diversity in the number of cryptocurrencies. Finally, three categories of low risk, good service, and financial advantage were introduced.

KEYWORDS

Digital Currency Exchange, Digital Currency, Exchange.

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Introduction

One of the main challenges of the world today is adapting to the development of technology and welcoming the ongoing industrial revolution, which is mainly digital in nature (Hashemi et al., 2022). Entering the era of digital economy shows the need to create changes and move towards digital transformation (Hosseinzadeh et al., 2022). Digital currency is a unique technological development that has attracted the increasing attention of researchers, investors, financial institutions, and legislators (Alsalmi et al., 2023).

Digital currency or as some others call it, cryptocurrency is basically a decentralized digital money designed to be used on the Internet and it was launched in 2008 (Ghosh et al., 2020). Removing border restrictions and creating a flow independent of the government's legal restrictions in trading markets is the main reason for the birth of digital currencies. By using digital currencies, you can do business in the financial markets of the world (Akhavan et al., 2020).

Bitcoin is the first digital currency presented and is still the largest, the most influential and the most well-known currency which was first introduced in an article by Satoshi Nakatomo (2008) and came of age in 2009. Since then, digital currency market has evolved dramatically (Makarov et al., 2020). Bitcoin technology and digital currencies are one of the most important human-made technologies in today's era. Governments, banks, and financial institutions have the ability to intervene in them (Ghosh et al., 2020).

Moreover, due to using Blockchain technology, it is highly secure and cannot be hacked. These are the reasons for using Bitcoin instead of money in financial transactions of the country in the conditions of sanctions and economic pressures. Another topic related to digital currency that has received a lot of attention is the topic of digital currency exchanges. Because the first step to start working and earn profit in the digital currency market is to choose a suitable exchange with superior features. A digital currency exchange is a platform where users and investors can convert their digital currencies into digital currency or national currency (Akhavan et al., 2020).

Today, there are more than 32, 374 digital currencies in the world markets that are traded in 51 international exchanges and the estimated market value of digital currencies in 2022 is more than 200 billion dollars (Alsalmi et al., 2023). Among them, Bitcoin had the most publicity and success. Bitcoin is the first peer-to-peer decentralized network and the main base code which was the highest operating currency in 2015. In 2016, it was reviewed as the best operational product (Ghosh et al., 2020). Today, more than 100,000 businesses in the world have accepted Bitcoin (Mallqui & Fernandes, 2019). The sooner business users understand how digital currencies affect global commerce, the sooner they can prepare themselves for a rapidly evolving financial landscape.

There are various factors and criteria for choosing an exchange for conducting digital transactions. It can be effective in decision making. Factors such as the security of the user interface, the support services, the volume of transactions, the number of tradable digital currencies, and transaction fees have been introduced as the most important factors in choosing an exchange for conducting digital transactions. In fact, compared to conventional currencies, digital currencies are still a relatively limited monetary phenomenon. Despite the increasing attention to digital currencies as digital assets, the existing literature still lacks empirical evidence (De Pace & Rao, 2023).

Several studies have been conducted in the field of digital currency exchanges and the factors affecting them, but despite this, these studies have examined the various dimensions of digital currency exchanges and their impact on digital currency, and a research has been conducted in connection with identifying suitable exchanges. Has not been therefore, the purpose of this research is to identify the effective factors in choosing digital currency exchanges.

Literature Review

Theoretical Foundations

1. Digital Currency

Digital currency or so-called crypto currency is basically decentralized digital money designed to be used on the Internet (Ghasemi, 2020). Cryptocurrency is equivalent to the word "cryptocurrency". This word consists of two parts "crypto" meaning encryption and "currency" meaning currency (Soltani Fard & Mohammadi, 2023). Cryptocurrencies have increased significantly in the past few years. They are digital currencies built on Blockchain technology that allow payment and other transactions to be confirmed in the absence of a centralized custodian (Makarov et al., 2020).

Cryptocurrencies with virtual currencies are relatively new forms of currencies that generally enable electronic payments between people without financial intermediaries and fee-free transactions. They typically provide aliases. Cryptocurrencies work on digital records, thanks to which it is possible to track and validate all payments at all times. They can be used as a decentralized payment system that is not controlled by any institution or central authority (De Pace & Rao, 2023).

Blockchain is a network that uses decentralized technologies and encryption to store the history of all transactions made by digital assets such as Bitcoin in a public digital ledger. It is not possible to change, cheat or manipulate the information stored in Blockchain, and all the information recorded in it is transparently provided to the users (Soltani Fard & Mohammadi, 2023).

Digital currencies are made of very complex codes and computer protocols for encryption. They use messages and transfers to provide safe transactions for its users. These protocols are developed based on the complex principles of mathematics and computer engineering to increase their security and make them unhackable. Additionally, by using these protocols, the identity of people who use digital currencies can be kept secret and prevented by other people and organizations. That’s why the rules of buying and selling digital currencies are different in different countries (Shirai, 2019; Shrivastva et al., 2020).

2. Cryptocurrency Wallet

Security is one of the most important challenges in digital currency exchanges. Many exchanges have been the target of cyber-attacks in the past, leading to the theft of large amounts of digital currency. To deal with these threats, many exchanges use security technologies such as two-factor authentication and digital currency storage in wallets (Chen & Liu, 2024). A digital currency wallet is a software program that stores private and public keys. This program interacts with various blockchains so that users can send and receive their digital currency and monitor their accounts (Halakoui & Heydarian, 2019).

Just as you keep your cash in a wallet or in a secure bank account, cryptocurrencies should also be kept in a wallet so that you can deposit and withdraw digital currency by creating an account in most of your exchanges. You will also have a dedicated wallet that has the ability to store various digital currencies and with the help of this dedicated wallet, you can deposit, withdraw, and transfer various cryptocurrencies inside the exchanges. Therefore, to start the activity of buying and selling digital currencies, you need to deposit the cryptocurrency into your wallet in the exchange so that your account can be recharged (Akhavan et al., 2021).

There are different ways to secure your private key which is called a digital currency wallet. There are different ways such as using software wallets, making virtual wallets in online exchanges, using online and web-based wallets, and using the Internet independent wallet etc to secure the user's private key. However, this method of storing coins is very dangerous, remember that you do not directly own your private key, that is, if the exchange is hacked, you may lose your coins. Several exchanges were hacked and a lot of currency was stolen, but this issue was not due to the difficulty of storing cryptocurrencies, this happened because people did not pay much attention to storage (Newfound & Kasperchik, 2020).

3. Digital Currency Exchange

A digital currency exchange is a platform where people can trade their digital currencies and convert them into another digital currency or national currency. The first digital currency exchange in Australia was launched in 2004. In the first years, due to the unknown nature of these platforms or illegal activities, these exchanges were not very prosperous and their activities were stopped by law. But now this exchange is accepted in most countries of the world and millions of people use it daily and they have a method for the cryptocurrency exchange (Mohammadi Armandi, 2020).

Digital currency exchange is a business that allows customers to trade digital currencies. Digital currency exchanges can be a market maker. A digital currency exchange is a business that allows customers to trade digital currencies. Cryptocurrency exchanges can be market makers, typically using the bid-ask spread as a commission for services or as a matching platform, charging fees (Gorgani Firouz Jaei et al., 2021). The exchanges perform the task of guaranteeing transactions and while accepting the risk of hundreds of exchanges (Pichler et al., 2020), they also undertake the conversion of currencies to facilitate the process (Xio et al., 2020).

In addition to the process of buying and selling currency between users, exchanges also play a role as buyers deduct a percentage from users in the form of fees. On the other hand, the digital currency exchange guarantees all transactions on its platform. For example, there may be problems in the conversion of some currencies, regardless of them, the exchange will convert all currencies into each other or the common currency of the country. One of the advantages of the exchange is the ability to work remotely. People can work according to their time in some exchanges and earn money with digital currency. Another service that some exchanges provide is the possibility of buying goods and services online. People can buy products in these exchanges using their digital currencies (Mohammadi Armandi, 2020).

4. Decentralized Exchanges

A digital currency exchange is a web platform or mobile software that can be used to buy and sell Bitcoin, Ethereum, and other altcoins. These exchanges often operate in two forms of decentralized (DEX) and centralized (CEX). But in general, there are three types of exchange for exchange. A centralized exchange that is run by a company or, the organization is managed by decentralized exchanges that provide an automated process for peer-to-peer transactions on blockchain network, and hybrid exchanges that combine both of the above (Xio et al., 2020).

A decentralized exchange is a platform for conducting decentralized transactions that uses blockchain and smart contracts to eliminate intermediaries. The users of these exchanges can make transactions from within their wallets without depositing their digital currencies into the exchange wallet. On the other hand, there are centralized exchanges that can be transacted automatically by charging the account and registering orders. In Iran, all the reliable digital currency exchanges are centralized (Asadi, 2015).

In decentralized exchanges, all transactions are conducted peer-to-peer and no individual or organization has control over the exchange, meaning that transactions are conducted directly between the payer and the recipient without the presence of a third party (Alsalmi et al., 2023).

The advantages that decentralized exchanges have over their centralized ones are lack of access and lack of control centers for users' assets. Therefore, the possibility of hacking and losing assets through hacker attacks is considered a low probability option in these types of exchanges (Fazli et al., 2018).

With a decentralized exchange, users will be able to make transactions from their own wallets without depositing digital currencies into the exchange's wallet. In this way, the existing restrictions and transaction fees are significantly reduced (Halakoui & Heydarian, 2019).

A decentralized exchange poses several challenges for traders. Some of the key challenges that traders face during decentralized exchanges are1. Lack of liquidity (liquidity constraints are one of the major challenges in DEX); 2. Slow trading; 3. Complexity of smart contract development; 4. Lack of margin trading; and 5. Security challenges (Akhavan et al., 2020).

Research Background

Zarei Kariani (2020) has investigated the role of decentralized hybrid synchrobit platforms and their features in the operation of digital exchanges. For this purpose, investigations using Confirmatory Factor Analysis (path analysis method) and smart PL2 software were used. The results showed that the transaction security feature and the user experience of decentralized hybrid syncrobit platforms have a positive and significant effect on digital currency exchanges.

Newfound and Kasperchik (2020) reviewed the basic theory of cryptocurrencies and everything that is needed to invest in cryptocurrencies in simple language. They have argued that users can minimize the risk and maximize the profit.

Ghosh et al. (2020) have investigated Blockchain structure and the performance of current transactions in digital currency network in the research of digital currency security in Blockchain technology, art, challenges, and future prospects. The results of their study included the detailed classification of Blockchain along with their features and their applications in real world.

Halakoui and Heydarian (2019) investigated the types of digital currencies and digital currency exchanges. They have provided the readers with an opportunity to easily enter the world of digital currency as a beginner, and introduced them step by step to the beautiful world of digital currencies, digital currency exchanges, and business methods of it. Mohammadi Armandi (2020) examined zero to one hundred virtual networks and explored digital currencies as well as digital currency exchanges from different dimensions. In his opinion, digital currencies are very surprising and unpredictable.

Ghasemi (2020) has investigated the performance of crypto currencies, their impact on economy, and the threats and opportunities of the development of this technology. In this research study, by studying the experience of three East Asian countries that are pioneers of this supply, using a descriptive and analytical method, he concluded that despite the strong opposition of governments to digital currency, today digital currencies have their place in banking structure and future of global trade.

Ghorbani and Naqadi Khodachah (2020) have investigated the future research of investment in the field of digital currencies by conducting a comparative comparison and hierarchical analysis of international exchanges. This study aimed to analyze and select the best exchange in the field of digital currencies with a future research perspective, which at first introduced the best digital currency exchanges and examined the strengths and weaknesses of each and the most important indicators and criteria in choosing an exchange. The results of this research can be used for future research and investment in the field of cryptocurrencies.

In another study, Akhavan et al. (2020) investigated the purchase of digital currencies and their conversion to another. Considering the difference of digital currencies from one another, converting them into one another creates problems. On the other hand, trading one with the other also has a platform for exchange. As a result, having a platform made it easier to buy, sell, and trade digital currencies.

Since not much time has passed since the invention and birth of digital currencies, the main issues that researchers have obtained during these few years are related to knowing more and more about this network. The surveys conducted are mostly related to digital currencies and researchers have less entered into the topic of digital currency exchange, therefore, in this study, the factors influencing the choice of digital currency exchange have been identified.

Methodology

The present study is a qualitative research in terms of method, exploratory in terms of approach, applied in terms of purpose and interpretive in terms of data collection or the nature and method of the research. The statistical population in this research is the digital currency traders (in Iran) who use digital currency exchanges, of which 16 people were interviewed. To select the participants, a purposive sampling method was used, following the rule of theoretical saturation, so that no new codes were found in the interviews and the codes became repetitive, which was considered sufficient and reached theoretical saturation.

Table 1 shows the demographic characteristics of the interview participants who were randomly selected from among the users of digital currency exchanges.

Table 1.
Demographic Characteristics of the Sample

Area of actity	Education	Age	Gender	Row	Area of activity	Education	Age	Gender	Row
Financial market analyst	master	39	man	9	Digital currency signal application	business and economics experts	28	man	1
Trader	bachelor	30	woman	10	Trader of digital currencies and physical gold	collegian	23	man	2
Trader	collegian	22	man	11	Education is Bitcoin	bachelor	31	woman	3
Digital currency exchange	bachelor	27	woman	12	Learning how to earn dollars in simple language	researchers of the Ministry of Communications	35	man	4
Trader	bachelor	30	man	13	Lecturer and trader of financial markets	master	33	man	5
Apoors Arzdigital	Ph.D.	40	man	14	Expert digital currency trader	bachelor	24	woman	6
Employee	bachelor	35	man	15	Forex/ digital currency	master	28	man	7
Accountant	bachelor	38	man	16	(Entrepreneur) digital currency training	bachelor	42	man	8

(Source: Researcher's Findings)

Interview was used as the data collection instrument in this study. The duration of each interview was between thirty minutes and one hour. The interview questions are as follows: 1. What are the factors and criteria in decision-making for choosing a digital currency exchange to conduct transactions? Can they be effective? 2. What factors cause trust in a digital currency exchange? 3. What factors should Iranian users pay more attention to when choosing digital currency exchanges? 4. What features should the best digital currency exchanges have for Iranian users? The method of data analysis in this research is theme analysis. In this study, methods such as using audio recording process, implementing interviews, and checking the research themes with expert researchers were examined to ensure the validity and reliability of the study.

Findings

Data analysis in this research was done using theme analysis method which includes 6 steps:

1. At this stage, the interviews were read in several stages and the contents and topics related to the purpose of the study were identified. Then, after mastering the interviews, coding and data analyzing began, and the data were typed and transcribed. Subsequently, each of the interviews was given an interview code.

2. In this step, the data specified in the previous step is coded. In fact, primary coding is used to reduce the volume of data and simplify them.

3. After the initial coding of all the interviews, the formed codes are refined and consolidated. Incomplete or unrelated codes as well as duplicate codes were left out until the final selective codes were obtained. In this study, 42 sub-themes were identified in the interviews and the codes of each interview were identified.

Table 2.
An Example of Extracting Initial Codes from the Interviews

Initial codes	Key results of the interview
Security	The security system of an exchange must be at the highest possible level so that the user can feel comfortable about the security of his assets.
Daily circulation volume, high account turnover	The volume or coin in circulation is the total number of digital currency coins and units of a cryptocurrency that are available for purchasing and selling in the market.
Support	Quick and online response during transactions (the exchange has no value and will not be stable if it does not respond to questions).
Learning, resume and background	The degree of popularity, the number of people working in an exchange.
Platform type	Support a variety of suitable platforms.
Features and futures	Futures are a way to profit from asset prices, including cryptocurrencies, without actually owning them. By using futures transactions, you can profit from both sides of the market (both from the fall in the price of digital currency and from the increase in the price of digital currency).

(Source: Researcher's Findings)

4. At this stage, the researchers put together the extracted codes that have the most semantic and conceptual affinity to each other and create new meanings and words, creating organizer themes which includes two steps of reviewing and refining the coded summaries as well as forming and validating these themes. In this study, there are 6

organizer themes including security, liquidity, and volume of transactions, support, authentication, fees, and diversity in the number of digital currencies. The themes were classified in these 6 categories based on their conceptual relationships with each other.

5. This stage introduces and explains the main themes of the research and specifies which aspects of the data each main and comprehensive theme contains; This means that all the themes and topics of the organizer that overlap are placed in one group and class. Accordingly, there are three main themes: 1. Low risk, 2. Appropriate services, and 3. Financial advantage.

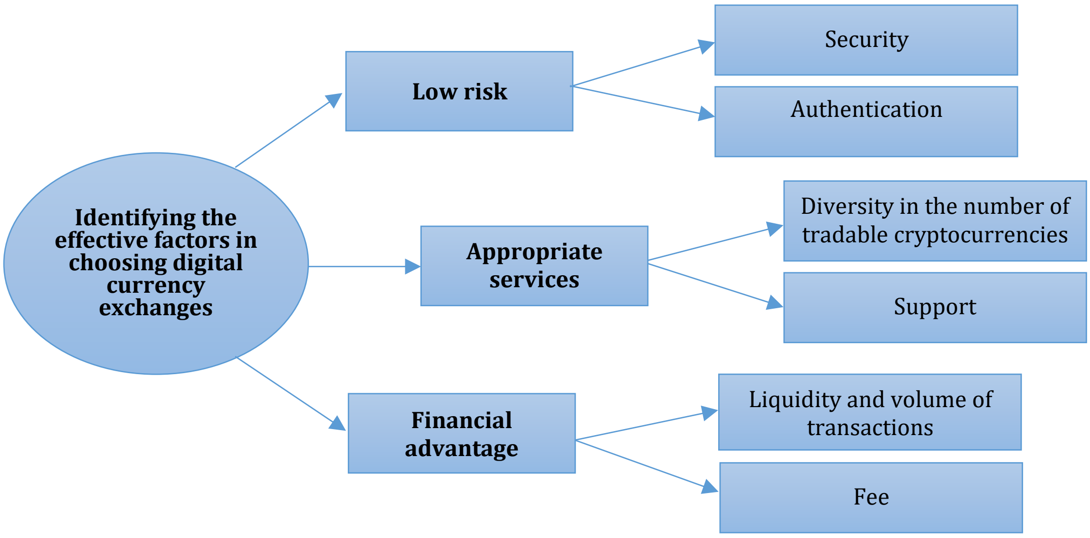
Table 3.
The Overarching Themes

Sub-themes	Organizer themes	Overarching themes
Observation of security matters		
Currency storage methods	Security	
Having official licenses		Low risk
Customer identification and confirmation		
No mandatory authentication	Authentication	
Fast and convenient authentication		
Support for different currencies		
Trading digital currency pairs		
The high number of altcoins of an exchange	Diversity of the number of tradable cryptocurrencies	
Having two-sided markets		
24-hour support		Appropriate services
Support for all languages	Support	
Online support		
Support for Iranian users		
High volume of transactions		
Daily turnover volume (account turnover)		
High investment	Liquidity and volume of transactions	Financial advantage
Settlement speed		
Low fee		
Exchange fee	Fee	

(Source: Researcher's Findings)

6. In the stage of preparing the report, based on the findings and coding done by the thematic analysis method, the conceptual model of the plan and the relationships between the factors affecting the choice of digital currency exchanges have been explained. Figure 1 shows the final research model in the qualitative section.

Figure 1.
Conceptual Framework of Factors Influencing the Selection of Cryptocurrency Exchanges



(Source: Researcher's Findings)

Discussion and Conclusion

With the emergence of Bitcoin and numerous cryptocurrencies in the last few years and their stunning growth and sometimes significant fluctuations, digital currencies gained momentum and a wide range of different strata showed interest in investing and trading them. Buying and selling cryptocurrencies needed a suitable and secure platform, where people can operate with ease and confidence. There are many platforms. They started working and many interested people have sought to learn how to work with these platforms and familiarize themselves with their various functions all over the world. In fact, there are different types of digital currency exchanges and the way they work is not the same, but they all have a specific purpose, which is to exchange, buy, and sell currencies. A number of 42 codes were identified in the interviews, which were placed in 6 organizing themes including liquidity, security, and high volume of transactions, authentication, support fee, and diversity in the number of tradable cryptocurrencies in a digital currency exchange. Finally, three main themes of1- low risk, 2- suitable services, and 3- financial advantage were recognized as the overarching themes of the main theme.

1. Low risk

Digital assets are a type of high-risk investment, and buying and selling them without a plan usually leadto capital loss. Investors and traders seek to reduce risk, and for this purpose, they identify and evaluate financial risks related to investment and choose strategies to reduce these risks. High security and strong authentication are very important factors in controlling the risk and lowering the transaction risk.

Security, plays a key role in increasing attitudinal and behavioral loyalty. Security is a very critical issue for a digital currency exchange, and without it, the users will not have any competitors to use the exchange services. In fact, security is a priority and when an exchange does not have security, it has no value. No Iranian exchange has any official license because the parliament has not passed or proposed any official law regarding it and it only has a license from the FATA police.

Compared to the previous research, this study also strengthens the previous studies (Akhavan, 2020; Fazli et al., 2018; Halakoui & Heydarian, 2019; Mohammadi Armandi, 2020; Zarei Kariani, 2020). The studies mentioned above also consider security as an important factor in choosing a digital currency exchange.

The process of authentication is the first step in the evaluation of musteh in the fight against money laundering. Many digital currency exchanges have required authentication on their platforms. In fact, the purpose of authentication is to increase security and prevent criminal and illegal activities and it creates trust and transparency in the digital currency ecosystem. The authentication process causes users living in sanctioned countries to be deprived of exchange services. The digital currency industry, which is based on anonymity and confidentiality, has contradictions.

This study has explored the previous studies (Akhavan, 2020; Fazli et al., 2018; Mohammadi Armandi, 2020) about identity authentication. The studies mentioned above also consider authentication as an important factor in choosing a digital currency exchange.

2. Proper performance

A digital currency exchange with suitable services is a type of digital currency service that allows individuals and investors to trade and exchange digital currencies with other digital currencies or national currencies of other countries and also has appropriate support for users, which is the most important feature of the best exchange.

In fact, users face many questions and errors regarding digital currencies, so they need someone to guide them to solve the problems. Inauthentic exchanges usually have limited support services. The best exchanges are the ones that have the most options to access the support team. The exchanges with excellent support are the exchanges that answer all the questions of their users online and 24 hours a day in all languages. Provide support in relation to Iranian users, it is very important for Iranians that exchanges support all their users (especially Iranians) and do not block their accounts and freeze their assets due to the sanctions. In fact, it is very important for Iranian users that foreign exchanges have support in Persian language.

Compared to the previous studies, this study also strengthens the previous studies (Akhavan, 2020; Fazli et al., 2018; Halakoui & Heydarian, 2019; Mohammadi Armandi, 2020) regarding support as one of the important and influential factors in choosing digital currency exchanges. The studies mentioned above also consider support as an important factor in choosing a digital currency exchange.

The more the number of currencies that an exchange supports the more open your hands are to make transactions and the more diverse transactions can be done. Such exchanges are usually more popular among users and more people use them. Of course, this does not mean that such exchanges are a better option. Many of the currencies offered in the exchange may be invalid or not profitable in the market. Two-way digital currency markets are one of the most promising markets.

The two-sidedness of the foreign exchange market is one of the factors that people are interested in. Iranian exchanges usually do not have two-sided markets, or if they exist, they work very poorly, such as the Nobitex exchange, which has a two-sided market. However, the number of its currencies is so low that it is practically useless and nobody welcomes it.

Compared to the previous research studies, this study also reinforces previous studies (Akhavan, 2020; Fazli et al., 2018; Halakoui & Heydarian, 2019; Mohammadi Armandi, 2020) regarding the diversity in the number of digital currencies as one of the important and influential factors in choosing digital currency exchanges. The studies mentioned above also vary in the number of digital currencies which is an important factor in choosing a digital currency exchange.

3. Financial advantage

One of the most important and basic reasons for investing in the digital currency market is that you can do international transactions with this and can earn profits at the dollar rate. They do not have high liquidity. They have more value in the eyes of users. High and low liquidity of fees is very important for users who do trading.

The volume of market transactions, dynamics, and price gap are considered important factors in digital currency exchange. In large transactions, the volume of transactions is an important factor. If the prices or fees are suitable in a market, but there is no suitable volume in the orders, a large number of orders with low volume should be removed, which increases the user's costs.

Compared to the previous studies, this study also strengthens the previous studies (Akhavan, 2020; Fazli et al., 2018; Mohammadi Armandi, 2020; Zarei Kariani, 2020) about liquidity and high transaction volume as one of the important and influential factors in choosing digital currency exchanges. The studies mentioned above also consider liquidity and high transaction volume as important factors in choosing a digital currency exchange.

All trading platforms in the world including digital currencies, charge a fee for the services they provide. Cryptocurrency exchange fees are very important for traders who trade continuously. If your goal of operating in the digital currency market is long-term investment and you do not make more transactions per year, the amount of the fee may not matter much to you; but the case is completely different for traders who may make many trades during the day. As a result, they have to pay more fees, so the amount of fees is a very important thing that all traders pay special attention to.

Compared to the previous studies, this study also strengthens the previous studies (Akhavan, 2020; Halakoui & Heydarian, 2019; Fazli et al., 2018; Mohammadi Armandi, 2020; Zarei Kariani, 2018). The studies mentioned above also consider the fee as an important factor in choosing a digital currency exchange.

Suggestions

According to the above results, the following items are suggested to users for managing digital currency exchanges:

1. The first advice to users is not to keep digital currencies in the exchange. Keep your assets in your digital wallet for long-term storage. In the next step, it is better to divide your assets in several exchanges so that you do not lose all your capital in case of a problem;
2. Setting a strong password is one of the most important security measures that must be followed in order to increase security;
3. Almost all exchanges allow their users to set a two-step password for their accounts;
4. Watch out for fake email pages and software;
5. An exchange without authentication may be a fraud and it shows that compliance with money laundering laws is not important;
6. Exchanges without authentication have a small market share and you cannot make professional transactions;
7. Exchanges without authentication may force authentication due to pressure from legal entities, and users, especially users of embargoed countries, may be forced to transfer their assets and pay transfer fees or even lose all their capital;
8. Interact with the support of internal exchanges and try not to buy and sell exchanges that have poor support;
9. Choose decentralized exchanges that support Iranian users;
10. Before investing, be sure to pay attention to whether it supports users living in Iran and is not dangerous;
11. Our advice to you is that you must use exchanges that have a 24-hour response;
12. Interact with the support of internal exchanges and try not to buy and sell exchanges that have poor support;
13. The important advice regarding the diversity in the number of cryptocurrencies that you should take seriously is that many worthless tokens can be found in these types of exchanges, so avoid buying and keeping them to avoid financial loss.

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Identifying and Ranking Barriers to Implementing Internet of Things in Food Supply Chains: A Case Study of Kalleh Company

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ABSTRACT

The implementation of Internet of Things (IoT) technology in food supply chains faces significant barriers that hinder its potential to enhance traceability, efficiency, and sustainability. This study identifies and analyzes these barriers by conducting a case study of Kalleh Company, a leading Iranian food producer, using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. Through conducting a literature review and expert interviews, 11 key barriers were categorized into technological, financial, human capital, regulatory, and infrastructural dimensions. The DEMATEL analysis revealed critical insights into the causal relationships among these barriers. Inadequate infrastructure emerged as the most prominent barrier, heavily influenced by financial constraints such as high implementation costs and limited funding access. Meanwhile, lack of interoperability was identified as the strongest causal barrier, creating systemic challenges by preventing seamless integration across IoT systems. Interestingly, while the shortage of skilled labor showed balanced influence/dependence, its high prominence underscored its operational significance. The study highlights the complex interdependencies among IoT adoption barriers, demonstrating that infrastructure limitations cannot be resolved without addressing the underlying financial and technological challenges. These findings suggest that successful implementation of IoT requires coordinated strategies addressing multiple dimensions simultaneously including standardization efforts, financial support mechanisms, and workforce development programs.

KEYWORDS

Adoption Barriers, Causal Analysis, DEMATEL Method, Food Supply Chains, Internet of Things (IoT).

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Introduction

The Internet of Things (IoT), a revolutionary technological paradigm, is rapidly transforming industries worldwide, and the food industry is no exception. The IoT, characterized by the interconnection of physical objects embedded with sensors, actuators, and software, enables data collection, analysis, and communication on an unprecedented scale. This interconnected network of devices facilitates real-time monitoring, automation, and data-driven decision-making, offering immense potential for enhancing efficiency, safety, and sustainability across various sectors. Recent research papers from 2020 to 2024 highlight the transformative potential of IoT in diverse applications, ranging from smart agriculture (Bhavana et al., 2024) to precision manufacturing (Javadi et al., 2024) and intelligent healthcare (Tarik et al., 2025). However, the adoption of IoT technologies within the food industry, a sector characterized by complex supply chains and stringent safety regulations, faces significant barriers. This introduction delves into the intricacies of the food industry supply chain, the transformative potential of IoT, and the critical need to address the challenges hindering its widespread adoption.

The food industry supply chain, a complex network spanning from farm to fork, involves numerous stages, each presenting unique challenges. From agricultural production and harvesting to processing, packaging, distribution, and retail, the journey of food products is fraught with potential risks and inefficiencies. Traditional methods often lack the real-time visibility and data-driven insights necessary for optimal management. Inefficient processes lead to significant food waste, estimated at one-third of all food produced globally (Betty et al., 2024), resulting in substantial economic losses and environmental damage. Furthermore, maintaining food safety and quality throughout the extended supply chain is paramount, requiring stringent monitoring and control measures to prevent contamination and ensure consumer safety. The lack of transparency and traceability in traditional systems makes it difficult to identify and address issues promptly, leading to product recalls and reputational damage. Research papers published between 2020 and 2024 underscore these challenges, emphasizing the need for innovative solutions to enhance food safety, reduce waste, and improve overall supply chain efficiency (Akinbamini et al., 2025; Tanwar et al., 2022; Vasanthraj et al., 2023). The integration of IoT technologies offers a promising pathway to address these critical issues.

The application of IoT in the food industry holds the potential to revolutionize various aspects of the supply chain. Smart sensors embedded in agricultural fields can monitor soil conditions, weather patterns, and crop health, enabling precision farming techniques that optimize resource utilization and enhance yields (Bhavana et al., 2024). Real-time data on crop growth and environmental factors allows farmers to make informed decisions regarding irrigation, fertilization, and pest control, minimizing waste and maximizing productivity. In processing facilities, IoT-enabled equipment can monitor temperature, humidity, and other critical parameters, ensuring optimal conditions for preserving food and preventing spoilage (Mawardi et al., 2023). Automated systems can streamline production processes, reducing labor costs and improving efficiency. During transportation and distribution, IoT devices can track the location and condition of food products, ensuring timely delivery and maintaining product quality. Real-time monitoring of temperature and humidity prevents spoilage and ensures food safety. At the retail level, smart shelves and inventory management systems can optimize stock levels, reducing waste and improving customer satisfaction. The integration of Blockchain technology with IoT further enhances transparency and traceability, providing immutable records of food products' journey from origin to consumption (Ahmad et al., 2024; Kaur et al., 2022; Tanwar et al., 2022). This enhanced visibility allows for rapid identification and resolution of issues, minimizing the impact of contamination or spoilage incidents. Numerous research papers published in recent years demonstrate the significant benefits of integrating IoT in various stages of the food supply chain, highlighting its potential to improve food safety, reduce waste, and enhance overall efficiency (Alsayat & Ahmadi, 2023; Javadi et al., 2024; Liu, 2024; Mashayekhy et al., 2022; Maulana et al., 2021; Rui & Sundram, 2024; Sun & Wang, 2022).

Despite the significant potential benefits, the adoption of IoT technologies in the food industry faces numerous barriers. High initial investment costs associated with implementing IoT infrastructure, including sensors, software, and communication networks, can be a significant deterrent, particularly for small and medium-sized enterprises (SMEs) (Judijanto et al., 2024; Kuaban et al., 2024; Rui & Sundram, 2024). The complexity of integrating various IoT devices and systems across the entire supply chain presents technical challenges, requiring specialized expertise and robust data management capabilities. Concerns regarding data security and privacy are also paramount, as sensitive information about food products and supply chain operations needs to be protected from unauthorized access and cyber threats (Al-garadi et al., 2018; Hu & Shu, 2023; Stoyanova et al., 2020; Tarik et al., 2025). Lack of standardization and interoperability among different IoT devices and platforms hinders seamless data exchange and integration, creating compatibility issues and limiting the effectiveness of IoT solutions. Regulatory compliance and the need to adhere to stringent food safety standards add further complexity to the implementation of IoT. The lack of awareness and understanding of IoT technologies among food industry stakeholders, including farmers, processors, distributors, and retailers, also hinders their adoption. Resistance to change and a lack of skilled personnel capable of managing and maintaining IoT systems further exacerbate the challenges. Research papers published between 2020 and 2024 extensively discuss these barriers, highlighting the need for addressing these challenges to facilitate wider adoption of IoT technologies in the food industry (Hao & Demir, 2024; Khan et al., 2024; Kuaban et al., 2024; Nozari & Nahr, 2022; Pai et al., 2020; Sharma et al., 2024; Solanki et al., 2023; Zhao et al., 2024).

Addressing the barriers to IoT adoption in the food industry is crucial for ensuring food safety, reducing waste, and improving overall supply chain efficiency. The economic benefits of implementing IoT technologies are substantial, including reduced costs, increased productivity, and enhanced profitability. Improved food safety and quality lead to increased consumer trust and brand loyalty, while reduced waste minimizes environmental impacts and promotes sustainability. The social benefits including improved working conditions, enhanced food security, and reduced health risks associated with foodborne illnesses are equally significant. The potential for innovation and technological advancements in the food industry is immense, with IoT playing a pivotal role in driving this transformation. However, realizing this potential requires a concerted effort from various stakeholders, including governments, industry organizations, technology providers, and research institutions. Policy support, including financial incentives and regulatory frameworks, is essential to encourage the adoption of IoT, particularly among SMEs. Investment in research and development is crucial to overcome technical challenges and develop cost-effective, interoperable, and secure IoT solutions. Education and training programs are needed to enhance the awareness and understanding of IoT technologies among food industry stakeholders. Collaboration and knowledge sharing among different actors in the food supply chain are essential to facilitate the seamless integration of IoT systems and ensure the successful implementation of IoT-based solutions. This research aims to contribute to this critical endeavor by identifying and ranking the barriers to IoT adoption, providing valuable insights for stakeholders to develop effective strategies for overcoming these challenges and realizing the full potential of IoT in the food industry.

Literature Review

To have a holistic view of the literature first the authors extract the most updated papers with a Bibliometrics approach (e.g., Farazmand et al., 2019; Nourahmadi et al., 2022; Rasti et al., 2024). Then, after reviewing them, the most related papers are selected for the current study. Rui and Sundram (2024) examined the role of emerging technologies namely Blockchain, the Internet of Things (IoT), and Artificial Intelligence (AI) in promoting the management of sustainable supply chain in Malaysia's food industry. Their research emphasized the benefits of these technologies in enhancing traceability, reducing waste, and improving efficiency. However, several barriers were identified, particularly for small and medium-sized enterprises (SMEs), including high implementation costs, lack of skilled labor, and concerns regarding data security and privacy. The authors suggested pilot programs, workforce training, and increased government support as key strategies for overcoming these obstacles. Similarly, Akinbamini et al. (2025) conducted a statistical analysis on the adoption of Supply Chain Collaboration Technologies (SCCTs) such as Blockchain, IoT, ERP, and AI within Nigeria's food industry. Their findings revealed that, despite the technologies' transformative potential, infrastructural deficiencies, regulatory constraints, weak trust-building mechanisms, and limited technical expertise hinder widespread adoption of IoT technologies. The study highlighted the importance of policy-driven interventions and targeted resource allocation to address these issues.

Virmani and Singh (2024) adopted the Best-Worst Method (BWM) and Graph

Theoretic Approach (GTA) to identify and prioritize the barriers to Blockchain adoption in agri-food supply chains. They found that technological barriers—particularly increased operational complexity and lack of interoperability were the most significant ones. They proposed a decision support framework to assist stakeholders in addressing these challenges systematically. Kumar et al. (2022) presented a comprehensive review on the integration of Blockchain and IoT technologies in food supply chains, emphasizing the barriers such as insufficient government regulation, low employee competency, and complex decision-making structures. These factors were found to significantly impact the rates of adoption.

Cuéllar and Johnson (2022) also explored the challenges of implementing Blockchain and IoT in agricultural supply chains, identifying poor infrastructure and limited user knowledge as major barriers. They argued that both the public and private sectors have a pivotal role in fostering the adoption of these technologies. Anusha and Padma (2021) investigated Blockchain applications in agriculture, pointing to benefits in traceability and smart contracts, but also noting limitations such as high energy costs, insufficient education, and immature technological infrastructure in the Indian context. Vern et al. (2023) conducted a broad review of barriers to Blockchain adoption in agri-food supply chains, noting that while IoT was not the main focus, its integration with Blockchain systems made the findings highly relevant. The study used multiple analytical methods to identify and rank the most influential barriers.

In another study, Tsai et al. (2023) utilized an interval-valued hesitant fuzzy DEMATEL approach to evaluate barriers to Blockchain adoption in Vietnam's agricultural supply chain. Their findings identified a lack of government regulation as the most critical impediment, underscoring the need for clearer policy frameworks. Nisar et al. (2024) explored the Chinese fisheries supply chain using a grey Delphi and DEMATEL approach, identifying regulatory compliance issues, high implementation costs, and the complexity of supply chain networks as key barriers to Blockchain adoption. Khan et al. (2022) employed the Best-Worst Method (BWM) to investigate the challenges of Blockchain implementation in food supply chains, revealing that technological and organizational barriers ranked highest in terms of influence. Wang et al. (2024) applied a hybrid interval-valued Fermatean fuzzy PROMETHEE-II model to analyze barriers to the adoption of resilient supply chain systems in the food sector. While not limited to IoT, the insights offered a broader understanding of the challenges associated with the adoption of advanced technologies in this industry.

Finally, Gonçalves et al. (2024) focused on SMEs and sustainable supply chain management (SSCM), identifying financial constraints—especially lack of funding—as major obstacles. Although not exclusively centered on IoT, the findings remain relevant given the investment-intensive nature of IoT integration. Singh et al. (2023) used a grey Delphi-DEMATEL approach to identify critical success factors for Blockchain-integrated IoT in food supply chains. They emphasized the importance of top management support, knowledge management, skilled personnel, technology readiness, and capital investment in enabling successful implementation.

Methodology

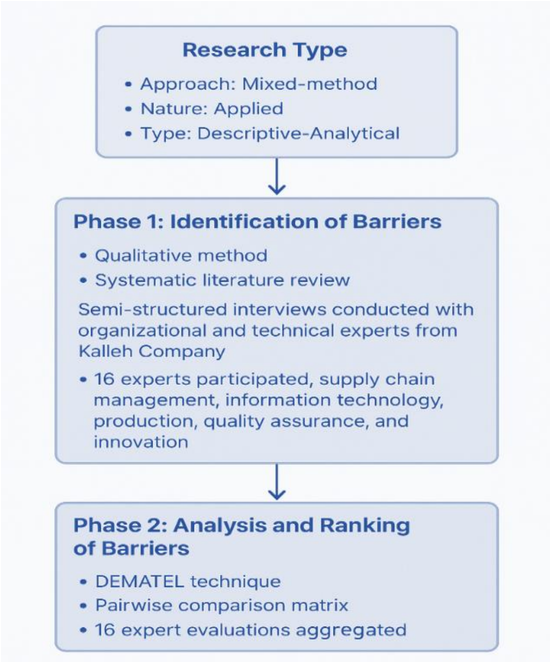
This study adopts a mixed-method and applied research approach (Sadeghi et al., 2013b). Given that the primary objective is to identify and rank the barriers to the implementation of Internet of Things (IoT) technology in the food supply chain and to analyze the causal relationships among them in a leading Iranian food company, the research is categorized as descriptive-analytical and falls within the scope of multi-criteria decision-making (MCDM) studies.

In the first phase, a qualitative method was used to identify the key barriers to IoT implementation. Initially, a comprehensive and systematic review of the literature was conducted to extract a preliminary list of potential barriers, but in some other research studies, it is common to use other qualitative methods to identify factors (Danaeefard et al., 2014; Danaeefard et al., 2015; Mostafazadeh & Sadeghi, 2014; Mostafazadeh et al., 2016; Sadeghi, et al., 2024). Next, to refine and validate this list, semi-structured interviews were conducted with organizational and technical experts from Kalleh Company. These experts were purposefully selected based on their familiarity and hands-on experience with technological projects and initiatives, particularly those related to implementing IoT. A total of 16 experts participated in this phase, all of whom held senior positions in areas such as supply chain management, information technology, production, quality assurance, and innovation. The decision to interview 16 experts was based on the principle of data saturation, where additional interviews were no longer yielding new insights or barriers. The participants had, on average, more than 10 years of professional experience and held at least a master’s degree in relevant fields such as management, industrial engineering, information technology, or agri-industrial sciences. To examine the validity of this research study, triangulation was applied by cross-referencing findings from literature with expert interviews to ensure consistency. Expert selection was purposive, ensuring relevance and experience, while their responses were validated by using consensus-building and repeated evaluations. Additionally, the use of the DEMATEL method, known for modeling complex interrelations, strengthened the construct validity of the study by mapping logical cause-effect relationships among barriers.

There are some techniques to rank factors in different research papers (Molavi et al., 2013; Sadeghi et al., 2013a; Seyed Javadein et al., 2013). In the second phase of the current research study, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique was employed to analyze the interrelationships among the identified barriers and to rank them based on their levels of influence and dependence. DEMATEL enables researchers to uncover and visualize the cause-and-effect structure among factors using expert judgments. The DEMATEL method was selected for this study because the barriers of IoT implementation are not isolated; they are interdependent and influence each other in complex ways. While AHP is effective for straightforward prioritization, it does not capture causal relationships between factors. DEMATEL, on the other hand, enables both the identification of influential (cause) and influenced (effect) barriers and their ranking based on their prominence (D+R), making it especially suitable for system-level analysis in complex environments like food supply chains.

For this purpose, a pairwise comparison matrix was developed with the participation of the same 16 experts. After aggregating their evaluations, the standard DEMATEL steps were followed to compute the direct-relation matrix, the total relation matrix, and the causal diagram. The final output enabled the classification and ranking of the barriers according to their influence and dependency degrees. The research methodology adopted in this study is illustrated in Figure 1.

Figure 1.
The Framework of Research Methodology of the Study



(Source: Researcher's Findings)

Findings

The barriers to IoT implementation in the food supply chain were identified through a comprehensive review of the literature and expert interviews. These barriers are presented in Table 1.

Table 1.
The Identified Barriers to IoT Implementation in the Food Supply Chain

Barrier Category	Specific Barrier	Detailed Description	Source
Technological Barriers	Lack of Interoperability	Difficulty in integrating IoT devices and systems from different vendors; lack of standardized protocols and data formats.	(Aamer et al., 2021; Ahmad et al., 2024; Buthelezi et al., 2022, pp. 1–32; Mohammed et al., 2023, pp. 14236–14255; Sarkar et al., 2024; Virmani & Singh, 2024)
	Technological Immaturity/Limitations	Existing technologies may not be sufficiently advanced or reliable for applications of specific food supply chain; limited sensor capabilities or data analytics tools.	(Aamer et al., 2021; Ahmad et al., 2024; Derakhti et al., 2023; Koshta et al., 2024, pp. 13096–13108; Luo et al., 2022; Rui & Sundram, 2024; Virmani & Singh, 2024; Yadav et al., 2023, pp. 1215–1224)
	Challenges of Data	Difficulty in collecting,	(Aamer et al., 2021; Chen et al., 2024;

Barrier Category	Specific Barrier	Detailed Description	Source
	Integration and Analysis	processing, and analyzing large volumes of data from diverse sources; lack of appropriate data management and analytics tools.	Derakhti et al., 2023; Luo et al., 2022; Rui & Sundram, 2024; Serrano-Torres et al., 2025; Sharma et al., 2024; Yadav et al., 2023, pp. 1215–1224)
	Inadequate Infrastructure (Technology)	Lack of reliable Internet connectivity, especially in remote areas; insufficient power supply for IoT devices.	(Aamer et al., 2021; Ahmad et al., 2024; Derakhti et al., 2023; Koshta et al., 2024, pp. 13096–13108; Luo et al., 2022; Rui & Sundram, 2024; Sarkar et al., 2024; Virmani & Singh, 2024; Yap et al., 2023, pp. 419–441)
Financial Barriers	High Implementation Costs	Significant upfront investments required for hardware, software, integration, and training; ongoing maintenance and operational expenses.	(Buthelezi et al., 2022, pp. 1–32; Delouyi et al., 2023; Mishra et al., 2023; Mohammed et al., 2023, pp. 14236–14255; Pratama, 2024; Raman & Selvaraj, 2024; Rui & Sundram, 2024; Sarkar et al., 2024; Selvaraj, 2025; Serrano-Torres et al., 2025; Singh et al., 2023; Virmani & Singh, 2024; Yadav et al., 2023, pp. 1215–1224; Yap et al., 2023, pp. 419–441; Zhao et al., 2024)
	Return on Investment (ROI) Uncertainty	Difficulty in quantifying the benefits of IoT adoption; long payback periods; lack of clear business cases.	(Mohammed et al., 2023, pp. 14236–14255; Pratama, 2024; Raman & Selvaraj, 2024; Rui & Sundram, 2024; Sarkar et al., 2024)
	Limited Funding/Access to Capital	SMEs and smallholder farmers often lack access to sufficient funding for IoT implementation.	(Delouyi et al., 2023; Mishra et al., 2023; Mumba & Mwanza, 2025; Raman & Selvaraj, 2024; Rui & Sundram, 2024; Sarkar et al., 2024; Selvaraj, 2025; Ullah et al., 2025; Yap et al., 2023, pp. 419–441)
Human Capital Barriers	Lack of Skilled Labor/Expertise	Shortage of personnel with the necessary technical skills to implement, manage, and maintain IoT systems; lack of data analytics expertise.	(Aamer et al., 2021; Ahmad et al., 2024; Akinbamini et al., 2025; Cuéllar & Johnson, 2022; Hangl et al., 2022; Koshta et al., 2024, pp. 13096–13108; Mishra et al., 2023; Mumba & Mwanza, 2025; Raman & Selvaraj, 2024; Rui & Sundram, 2024; Selvaraj, 2025; Singh et al., 2023; Susanty et al., 2024, pp. 11–15; Yadav et al., 2023, pp. 1215–1224; Yap et al., 2023, pp. 419–441)
	Resistance to Change/Lack of Awareness	Reluctance of stakeholders to adopt new technologies; lack of understanding of the benefits of IoT; insufficient training and support.	(Aamer et al., 2021; Akinbamini et al., 2025; Hangl et al., 2022; Jamaluddin et al., 2024; Julian & Ameliana, 2024; Mumba & Mwanza, 2025; Rui & Sundram, 2024; Singh et al., 2023; Yadav et al., 2023, pp. 1215–1224; Yap et al., 2023, pp. 419–441; Zafar, 2024)
Regulatory Barriers	Lack of Clear Regulations/Standards	Absence of clear guidelines and standards for data security, privacy, and interoperability; inconsistent regulations across different jurisdictions.	(Ahmad et al., 2024; Akinbamini et al., 2025; Jamaluddin et al., 2024; Julian & Ameliana, 2024; Koshta et al., 2024, pp. 13096–13108; Kumar et al., 2022; Mohammed et al., 2023, pp. 14236–14255; Pratama, 2024; Selvaraj, 2025; Susanty et al., 2024, pp. 11–15; Yap et al., 2023, pp. 419–441)
	Complex Compliance Requirements	Difficulty in meeting various regulatory requirements related to data security, food safety, and traceability.	(Ahmad et al., 2024; Akinbamini et al., 2025; Jamaluddin et al., 2024; Julian & Ameliana, 2024; Mohammed et al., 2023, pp. 14236–14255; Pratama, 2024; Selvaraj, 2025; Susanty et al., 2024, pp. 11–15; Yap et al., 2023, pp. 419–441)

(Source: Researcher's Findings)

Experts provided pairwise comparisons between the barriers using a scale from 0 (no influence) to 4 (very high influence). The resulting values were organized into an initial direct-relation matrix (Table 2).

Table 2.
The Initial Direct-Relation Matrix for IoT Implementation Barriers

Barrier	Lack of Interoperability	Technological Immaturity/Limitations	Challenges of Data Integration and Analysis	Inadequate Infrastructure	High Implementation Costs	ROI Uncertainty	Limited Funding/Access to Capital	Lack of Skilled Labor/Expertise	Resistance to Change/Lack of Awareness	Lack of Clear Regulations/Standards	Complex Compliance Requirements
Lack of Interoperability	0.00	4.00	2.00	4.00	4.00	1.00	2.00	2.00	2.00	4.00	3.00
Technological Immaturity/Limitations	2.00	0.00	1.00	3.00	1.00	3.00	4.00	0.00	3.00	1.00	4.00
Challenges of Data Integration and Analysis	3.00	0.00	0.00	2.00	2.00	1.00	3.00	3.00	2.00	3.00	3.00
Inadequate Infrastructure	0.00	2.00	4.00	0.00	4.00	0.00	1.00	3.00	0.00	3.00	1.00
High Implementation Costs	1.00	0.00	1.00	4.00	0.00	3.00	3.00	3.00	3.00	4.00	2.00
ROI Uncertainty	0.00	3.00	1.00	3.00	1.00	0.00	3.00	4.00	1.00	1.00	3.00
Limited Funding/Access to Capital	1.00	1.00	3.00	3.00	0.00	4.00	0.00	1.00	4.00	1.00	0.00
Lack of Skilled Labor/Expertise	3.00	3.00	3.00	4.00	0.00	4.00	4.00	0.00	0.00	0.00	0.00
Resistance to Change/Lack of Awareness	3.00	2.00	2.00	0.00	2.00	2.00	0.00	2.00	0.00	1.00	1.00
Lack of Clear Regulations/Standards	0.00	3.00	0.00	3.00	1.00	0.00	4.00	2.00	3.00	0.00	2.00
Complex Compliance Requirements	0.00	2.00	4.00	2.00	0.00	4.00	1.00	2.00	0.00	1.00	0.00

(Source: Researcher's Findings)

The initial matrix was normalized by dividing all elements by the maximum row or column sum, ensuring that the sum of each row or column does not exceed one (see Table 3).

Table 3.
The Normalized Direct-Relation Matrix

Barrier	Lack of Interoperability	Technological Immaturity/Limitations	Challenges of Data Integration and Analysis	Inadequate Infrastructure	High Implementation Costs	ROI Uncertainty	Limited Funding/Access to Capital	Lack of Skilled Labor/Expertise	Resistance to Change/Lack of	Lack of Clear Regulations/Standards	Complex Compliance Requirements
Lack of Interoperability	0.00	0.14	0.07	0.14	0.14	0.04	0.07	0.07	0.07	0.14	0.11
Technological Immaturity/Limitations	0.07	0.00	0.04	0.11	0.04	0.11	0.14	0.00	0.11	0.04	0.14
Challenges of Data Integration and Analysis	0.11	0.00	0.00	0.07	0.07	0.04	0.11	0.11	0.07	0.11	0.11
Inadequate Infrastructure	0.00	0.07	0.14	0.00	0.14	0.00	0.04	0.11	0.00	0.11	0.04
High Implementation Costs	0.04	0.00	0.04	0.14	0.00	0.11	0.11	0.11	0.11	0.14	0.07
ROI Uncertainty	0.00	0.11	0.04	0.11	0.04	0.00	0.11	0.14	0.04	0.04	0.11
Limited Funding/Access to Capital	0.04	0.04	0.11	0.11	0.00	0.14	0.00	0.04	0.14	0.04	0.00
Lack of Skilled Labor/Expertise	0.11	0.11	0.11	0.14	0.00	0.14	0.14	0.00	0.00	0.00	0.00
Resistance to Change/Lack of Awareness	0.11	0.07	0.07	0.00	0.07	0.07	0.00	0.07	0.00	0.04	0.04
Lack of Clear Regulations/Standards	0.00	0.11	0.00	0.11	0.04	0.00	0.14	0.07	0.11	0.00	0.07
Complex Compliance Requirements	0.00	0.07	0.14	0.07	0.00	0.14	0.04	0.07	0.00	0.04	0.00

(Source: Researcher's Findings)

The total relation matrix was obtained by applying the DEMATEL transformation formula (see Table 4). It reflects both direct and indirect influences among the barriers.

Table 4.
The Total Relation Matrix Representing Direct and Indirect Influences

Barrier	Lack of Interoperability	Technological Immaturity/Limitations	Challenges of Data Integration and Analysis	Inadequate Infrastructure	High Implementation Costs	ROI Uncertainty	Limited Funding/Access to Capital	Lack of Skilled Labor/Expertise	Resistance to Change/Lack of	Lack of Clear Regulations/Standards	Complex Compliance Requirements
Lack of Interoperability	0.14	0.35	0.31	0.44	0.30	0.28	0.35	0.31	0.27	0.34	0.31
Technological Immaturity/Limitations	0.17	0.17	0.23	0.33	0.17	0.29	0.33	0.20	0.25	0.19	0.29
Challenges of Data Integration and Analysis	0.22	0.18	0.20	0.31	0.20	0.23	0.32	0.30	0.22	0.27	0.26
Inadequate Infrastructure	0.11	0.21	0.29	0.21	0.24	0.17	0.23	0.27	0.14	0.24	0.17
High Implementation Costs	0.15	0.19	0.24	0.38	0.14	0.30	0.33	0.31	0.26	0.30	0.23
ROI Uncertainty	0.11	0.26	0.22	0.32	0.15	0.19	0.30	0.30	0.17	0.17	0.24
Limited Funding/Access to Capital	0.14	0.18	0.26	0.29	0.12	0.28	0.17	0.20	0.26	0.17	0.14
Lack of Skilled Labor/Expertise	0.21	0.27	0.30	0.37	0.14	0.32	0.35	0.20	0.16	0.17	0.17
Resistance to Change/Lack of Awareness	0.19	0.20	0.21	0.19	0.17	0.21	0.17	0.21	0.12	0.16	0.16
Lack of Clear Regulations/Standards	0.10	0.24	0.16	0.28	0.14	0.17	0.30	0.21	0.23	0.12	0.19
Complex Compliance Requirements	0.09	0.20	0.28	0.25	0.10	0.27	0.21	0.22	0.11	0.15	0.13

(Source: Researcher's Findings)

The prominence (D+R) and relation (D−R) values were calculated for each barrier (see Table 5). Barriers with positive D−R values are classified as causes, while those with negative values are considered as effects.

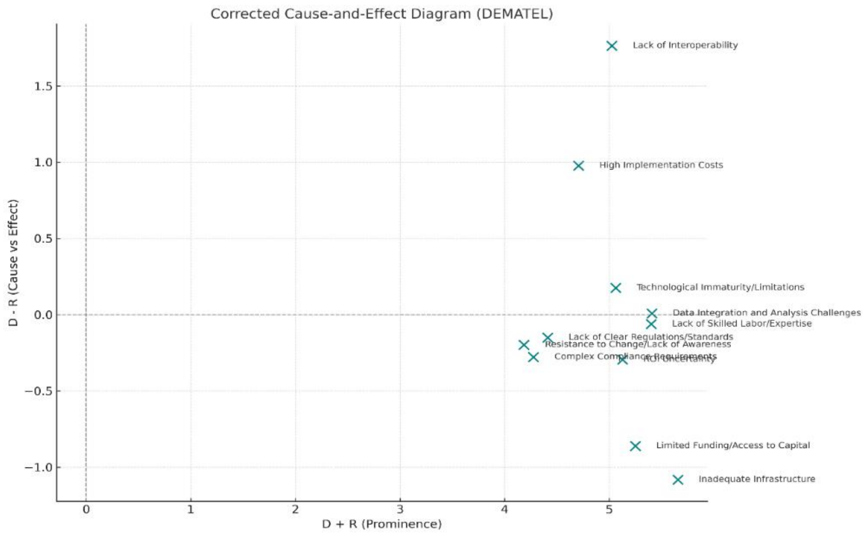
Table 5.
D, R, D+R, and D−R Values for Each Barrier

Barrier	D (Dispatching)	R (Receiving)	D+R (Prominence)	D−R (Relation)
Lack of Interoperability	3.40	1.63	5.03	1.76
Technological Immaturity/Limitations	2.62	2.44	5.06	0.18
Challenges of Data Integration and Analysis	2.71	2.70	5.41	0.01
Inadequate Infrastructure	2.29	3.37	5.66	-1.08
High Implementation Costs	2.84	1.87	4.71	0.98
ROI Uncertainty	2.42	2.71	5.13	-0.29
Limited Funding/Access to Capital	2.19	3.06	5.25	-0.86
Lack of Skilled Labor/Expertise	2.67	2.73	5.40	-0.06
Resistance to Change/Lack of Awareness	1.99	2.19	4.19	-0.20
Lack of Clear Regulations/Standards	2.13	2.28	4.41	-0.15
Complex Compliance Requirements	2.00	2.28	4.28	-0.28

(Source: Researcher's Findings)

A two-dimensional graph (Figure 2) was drawn with D+R on the x-axis and D−R on the y-axis to visualize the barriers' prominence and causal roles in the system.

Figure 2.
Cause-and-Effect Diagram Based on DEMATEL Analysis



(Source: Researcher's Findings)

The DEMATEL analysis reveals critical insights into the barriers hindering IoT implementation in the food supply chain. The findings demonstrate a clear distinction between causal and effect barriers, with lack of interoperability emerging as the strongest causal factor (D−R=1.76), significantly influencing other barriers through incompatible protocols and data formats that hinder the system integration. High implementation costs (D−R=0.98) create substantial financial barriers, particularly for SMEs, by requiring considerable upfront investments in hardware and software, while technological immaturity (D−R=0.18) reflects limitations in sensor durability and analytics capabilities that constrain IoT applications in perishable food environments. On the effect side, inadequate infrastructure (D−R=-1.08, D+R=5.66) stands out as the most prominent yet dependent barrier, where poor connectivity and power supply issues, exacerbated by funding shortages, create foundational challenges across the supply chain. Limited access to funding (D−R=-0.86) directly results from ROI uncertainties and high initial costs, creating a cyclical financing gap that further compounds the implementation difficulties. ROI uncertainty itself (D−R=-0.29) stems from technological immaturity and data integration challenges, making benefit quantification particularly challenging for stakeholders. The prominence values establish infrastructure deficiency (D+R=5.66) as the most critical operational challenge, demanding immediate attention as unreliable connectivity fundamentally undermines all potential IoT applications throughout farm-to-fork stages. Data integration challenges (D+R=5.41) highlight the pressing need for unified analytics platforms capable of processing heterogeneous IoT data streams, while skills shortages (D+R=5.40) reveal an urgent human capital gap in IoT system management and data science capabilities that must be addressed. Regulatory ambiguity (D+R=4.41), though less prominent, creates significant compliance risks that deter investment when combined with high implementation costs (D+R=4.71), presenting a complex challenge for policymakers and industry leaders. The analysis uncovers important interdependence dynamics, particularly a financial constraint loop where high costs lead to capital shortages, which in turn create infrastructure gaps that reduce ROI visibility. Similarly, a technological bottleneck emerges where immature solutions cause interoperability failures that result in data silos and ultimately resistance to adoption (D+R=4.19). These findings corroborate the existing literature on technology adoption challenges while providing new insights into the specific dynamics of IoT implementation in food supply chains. The unique positioning of infrastructure as both highly prominent (D+R=5.66) and highly dependent (D−R=-1.08) suggests it cannot be effectively resolved without first addressing the underlying financial and technological barriers, highlighting the need for comprehensive, system-wide strategies rather than isolated solutions. The results emphasize that overcoming these implementation barriers requires coordinated efforts across the technological development, financial support mechanisms, and workforce training programs to create an enabling environment for IoT adoption in the food supply chain sector.

Discussion and Conclusion

This study revealed that implementing IoT technology in the food supply chain faces multidimensional and interconnected challenges. The findings demonstrated that barriers operate as a complex system with causal interdependencies, meaning that addressing one challenge often requires simultaneous consideration of others. The DEMATEL analysis identified "inadequate infrastructure" as the most critical barrier, with the highest D+R value (5.66). This aligns with prior research on emerging technologies in food supply chains. However, a key insight from this study is that infrastructure limitations are themselves influenced by causal factors such as "high implementation costs" and "limited funding access". This finding carries important policy implications, suggesting that merely investing in physical infrastructure without addressing the underlying financial constraints will yield limited success. Among causal barriers, "lack of interoperability" emerged as the strongest driver (D−R=1.76). The absence of unified standards and communication protocols exacerbates other implementation challenges, reinforcing findings from international studies and underscoring the need for harmonized technical frameworks.

Notably, "lack of skilled labor" presents an interesting paradox. While its near-neutral D−R value (−0.06) indicates balanced influence/dependence, its high prominence (D+R=5.40) signals a substantial operational impact. This suggests workforce development should remain a priority despite its intermediate position in the causal network. The study ultimately demonstrated that overcoming IoT adoption barriers requires holistic, systems-level strategies rather than isolated interventions. Policymakers and industry leaders should prioritize:

- Encourage collaboration between food industry associations, tech companies, and regulatory bodies to create a national IoT interoperability framework tailored to agriculture and food sectors.
- Establish pilot programs using open-source platforms and standard communication protocols (e.g., MQTT, CoAP) to demonstrate integration feasibility.
- Incentivize vendors to adopt or align with internationally recognized standards (e.g., ISO/IEC 30141) through certification or government-backed endorsement programs.
- Launch government-subsidized grant or low-interest loan schemes specifically for SMEs adopting IoT in food supply chains.
- Develop public-private partnerships to co-finance infrastructure upgrades and IoT deployment in underserved regions.
- Provide tax credits or deductions for investments in IoT-related technologies and training, especially for smallholder producers.
- Collaborate with universities, vocational institutions, and IoT firms to offer modular training programs focused on IoT installation, maintenance, and data analytics.
- Introduce industry-specific certification programs to upskill current employees in the food supply chain.

- Leverage e-learning platforms and mobile apps to deliver flexible, localized training to rural and remote stakeholders.

Limitations of the Study

Despite providing valuable insights, this study has several limitations. First, the research is based on a single-case study of Kalleh Company, which may limit the generalizability of the findings to other companies or regions. While Kalleh offers a representative context, food supply chains vary significantly across countries and industry segments. Second, the reliance on expert judgment for the DEMATEL analysis, though rigorous, introduces subjectivity and may reflect organizational biases or specific experiences rather than sector-wide realities. Lastly, the study primarily focuses on internal and technical barriers; broader environmental and geopolitical factors (e.g., trade policies, macroeconomic instability) were not explicitly examined but may significantly impact IoT adoption. Future research should explore multi-case comparisons across different countries and integrate broader systemic factors for a more holistic understanding.

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Identification and Prioritization of Industry 4.0 Technologies in Maritime Industries Using Best-Worst Method (BWM)

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ABSTRACT

The Fourth Industrial Revolution (Industry 4.0) has provided significant opportunities to improve performance and productivity in maritime industries through emerging technologies. However, the multiplicity and diversity of these technologies have turned their selection and prioritization into a fundamental challenge for decision-makers. This research study aims to identify and prioritize key Industry 4.0 technologies in maritime industries. Through conducting a systematic literature review and interviews with 15 industry experts, 59 applications within 12 key technologies were identified. Then, using the Best-Worst Method (BWM) of multi-criteria decision-making, the relative importance of technologies and their applications were determined. The results showed that Digital Twin Systems with a weight of 20.02 is the most important technology, followed by Robotics and Automation with a weight of 16.11, and Artificial Intelligence (AI) and Machine Learning with a weight of 12.08. Among the applications, operation optimization through scenario testing, autonomous vehicle guidance in port areas, and staff training with virtual models obtained the highest priorities. By providing a systematic framework for technology prioritization, this research can assist decision-makers in maritime industry to allocate optimal resources and reduce investment risks.

KEYWORDS

Artificial Intelligence, Digital Twin Systems, Fourth Industrial Revolution, Maritime Industries, Robotics and Automation.

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Introduction

The Fourth Industrial Revolution, as a significant transformation in the digital era, is characterized by the integration of emerging technologies into industrial processes. This revolution, also known as Industry 4.0, is founded on the integration of cyber-physical systems, Internet of Things (IoT), cloud computing, Artificial Intelligence (AI), and other advanced technologies (Rüßmann et al., 2015). The concept of Industry 4.0, first introduced in Hanover Fair in Germany in 2011, has now become the dominant paradigm in the digital transformation of various industries, offering a novel approach to optimizing production processes and services (Berns et al., 2017). This revolution emerged with the aim of creating smart factories, flexible manufacturing, and supply chain optimization, and has rapidly expanded to other industrial domains.

Meanwhile, maritime industries, as one of the main pillars of the global economy, face numerous challenges in productivity, competitiveness, and sustainability. Statistics from the World Trade Organization show that more than 90 percent of global trade volume is conducted through maritime transport, with an annual growth rate of 3 to 4 percent (Yang et al., 2018). This enormous volume of commercial exchanges, accompanied by increasing competitive pressures, stringent environmental requirements, the need to reduce fuel consumption and emissions, and the necessity to enhance operational safety, requires new approaches in management and operations (Acciaro et al., 2018).

Emerging Industry 4.0 technologies offer significant potential to address these challenges. Studies indicate that implementing these technologies can lead to a 15 to 20 percent increase in operational productivity and a 30 percent reduction in maintenance costs (Chu et al., 2018). For example, the use of automated systems in port operations, AI in predicting vessel arrival times, IoT in equipment monitoring, and digital twin systems in operating simulation has created a fundamental transformation in the efficiency and effectiveness of the operations. Additionally, the use of augmented reality-based technologies in employee training and maintenance, and the application of Blockchain in supply chain management, have opened new horizons in the management of this industry.

The successful experience of leading global ports in implementing Industry 4.0 technologies demonstrates the significant potential of this digital transformation. For instance, the Port of Rotterdam, by implementing digital twin systems, has reported a 25 percent increase in operational productivity (PTI, 2019). The Port of Singapore, with the implementation of advanced automation projects and autonomous vehicles, has achieved a 20 percent reduction in container loading and unloading time (Woo, 2018). The Port of Hamburg has implemented an integrated traffic management and pollution control system using 5G and IoT (Krantz, 2017).

However, the multiplicity and diversity of available technologies have made their selection and prioritization a fundamental challenge for decision-makers. The high initial investment costs, which can sometimes reach hundreds of millions of dollars, limitations in human and financial resources, technical complexities of implementation, cyber-security issues, and the need for extensive workforce training, double the importance of making the right decisions in technology selection. This issue requires a systematic approach to identify and prioritize various technologies (Boyes et al., 2016; Vanelslander et al., 2019).

A review of the literature shows that previous studies have mainly focused on technical aspects or case applications (Xisong et al., 2013; Jardas et al., 2018). Some studies have examined the application of specific technologies such as AI or IoT in specific sectors of maritime industries (Kim, 2017; Rodič, 2017), while others have only addressed technical aspects of their implementation (Lu, 2017; Pérez-Lara et al., 2018). Thus, there is a significant gap in comprehensive decision-making frameworks for selecting and prioritizing these technologies. This research gap reveals the necessity of adopting a scientific and systematic approach to analyze and prioritize emerging Industry 4.0 technologies in maritime industries.

Accordingly, the present research has been conducted with the aim of analyzing and prioritizing emerging Industry 4.0 technologies in maritime industries. This study, utilizing the Best-Worst Multi-Criteria Decision-Making method, provides a systematic approach for evaluating and ranking these technologies. The Best-Worst method was chosen due to its capabilities in consistent pairwise comparisons, reducing the number of comparisons needed, and reliable results. The findings of this research study can serve as a scientific framework for decision-making in selecting and implementing Industry 4.0 technologies in maritime industries.

Literature Review

Industry 4.0

Industry 4.0 is a comprehensive concept that encompasses a set of emerging technologies for digitizing and creating intelligent industrial processes. This industrial revolution, first introduced in Hanover Fair in Germany in 2011, has created a fundamental transformation in the way products and services are produced and delivered by focusing on the integration of physical and digital systems. Boyes et al. (2016) in their comprehensive study on the impact of Industry 4.0 on organizational performance demonstrated that implementing these technologies can lead to a 25 to 35 percent increase in operational productivity.

Li (2018) showed that Industry 4.0, by integrating advanced technologies such as AI, IoT, cloud computing, and digital twin systems, provides the possibility of creating fully intelligent production environments. These intelligent environments are capable of making automated decisions and optimizing processes using real-time data. Xiu and Chen (2021) found that using Industry 4.0 technologies can reduce the operational costs by up to 20 percent and increase the production flexibility by up to 50 percent.

Tang et al. (2022) examined the impact of Industry 4.0 on global supply chain. The findings showed that this industrial revolution can increase supply chain flexibility by up to 45 percent through digitizing processes, improving transparency, and increasing traceability. Additionally, their findings showed that implementing Industry 4.0

technologies can reduce response time to market changes by up to 35 percent and improve demand forecasting accuracy by up to 40 percent.

Key Technologies of Industry 4.0

Internet of Things (IoT), as one of the main foundations of Industry 4.0, plays a central role in making industries intelligent. Jayavardhana et al. (2013) showed that IoT, through a network of sensors and communication systems, enables real-time data collection and intelligent control of processes. This technology provides a comprehensive view of the operational status of systems by creating connections between different equipment. Wang et al. (2018) found that using IoT in industrial environments can lead to a 40 percent reduction in equipment downtime and a 25 percent increase in energy efficiency.

AI and Machine Learning are key technologies of Industry 4.0. Kosova and Ünver (2022) demonstrated that these technologies, using advanced algorithms, are capable of analyzing massive volumes of industrial data and identifying complex patterns in industrial processes. According to existing studies, the use of AI in industrial processes can lead to significant improvements in operational efficiency and equipment failure prediction.

Blockchain, as another key technology of Industry 4.0, has created a fundamental transformation in managing industrial processes and supply chains. Studies by Harsha Vardhan et al. (2023) and Turgay and Erdoğan (2023) showed that this technology provides the possibility of transparent and reliable process tracking by creating a decentralized and immutable record system. This technology helps improve transaction speed by eliminating intermediaries and automating verification processes.

Digital Twin Systems are also recognized as one of the most advanced technologies of Industry 4.0. Liu (2023) and Tao et al. (2018) concluded that these systems provide the possibility of simulation and optimization of processes before their implementation by creating a virtual version of the physical environment. These systems can help reduce product design time and development costs and provide the opportunity to test different scenarios in a virtual environment without any risk.

Applications of Industry 4.0 in Maritime Industries

In the maritime industry sector, Industry 4.0 technologies have found extensive applications. Yang et al. (2018) argued that using IoT in port management can lead to a 35 percent improvement in loading and unloading operations efficiency. This improvement is achieved through real-time monitoring of equipment, container tracking, and intelligent port traffic management. Woo (2018) investigated the application of AI in maritime fleet management. He found that this technology can reduce the fuel consumption by up to 15 percent and increase the operational safety by up to 40 percent.

Chu et al. (2018) conducted a comprehensive review of automated ports. They found that using smart cranes and autonomous vehicles can increase the operational productivity by up to 45 percent. In this regard, the Port of Singapore, as one of the pioneers in port automation, has been able to reduce container loading and unloading time by up to 30 percent by employing advanced robotic systems. Kamolov and Park

(2019) explored the automated ship guidance systems and found that these systems can reduce the berthing operation time by up to 25 percent and improve operational safety by up to 50 percent.

Digital Twin Systems have various applications in maritime industries. Zhang and Chen (2020) argued that these systems provide the opportunity to optimize operations before implementation by simulating the performance of ships and port equipment in a virtual environment. Their research showed that using Digital Twins in port operations planning can lead to a 20 percent reduction in waiting times and a 35 percent improvement in resource allocation.

Blockchain has also created a fundamental transformation in maritime supply chain management. Li (2018) examined Blockchain applications in maritime transport. He concluded that this technology can reduce the document processing time by up to 70 percent and administrative costs by up to 40 percent. Additionally, the use of smart contracts in port operations provides the possibility of automating business processes and reducing human errors.

A review of previous research shows that despite the existence of extensive studies in the field of Industry 4.0 and its applications in maritime industries, there is a significant gap in prioritizing and selecting these technologies. Most studies conducted have either examined a specific technology on a case-by-case basis (Kim, 2017; Rodič, 2017) or have only focused on technical aspects of implementation (Lu, 2017; Pérez-Lara et al., 2018). Meanwhile, decision-makers in maritime industries need a comprehensive framework for evaluating and prioritizing these technologies. High investment costs, technical complexities of implementation, and resource limitations double the importance of making the right decisions in selecting the appropriate technologies. Therefore, the present research study has been conducted with the aim of filling this research gap and providing a systematic framework for prioritizing Industry 4.0 technologies in maritime industries.

Table 1.
Key Studies and Identified Industry 4.0 Technologies from Systematic Literature Review

Study	Focus Area	Technologies Identified
Rüßmann et al. (2015)	General framework for Industry 4.0	AI, IoT, Cloud Computing, Digital Twin Systems, Robotics
Boyes et al. (2016)	Cyber-security in maritime	Cyber-security, IoT, Cloud Computing
Yang et al. (2018)	Smart ports	IoT, Big Data Analytics, Digital Twin Systems
Vanelslander et al. (2019)	Maritime innovation	Blockchain, Automation, Robotics
Woo (2018)	Port automation	Robotics and Automation, AI
Li (2018)	Blockchain applications	Blockchain, Smart Asset Management
Chu et al. (2018)	Automated ports	Robotics, AI, IoT
Xiu & Chen (2021)	Smart manufacturing	Digital Twin Systems, 3D Printing, AR
Tang et al. (2022)	Supply chain flexibility	Blockchain, Cloud Computing, Big Data
Tao et al. (2018)	Digital Twin applications	Digital Twin Systems, IoT, AR
Kim (2017)	Cyber-physical systems	IoT, Cyber-security, Cloud Computing
Zhang & Chen (2020)	Smart ports	Digital Twin Systems, Big Data Analytics

(Source: Researcher's Findings)

Methodology

The philosophy underpinning this research study is pragmatism, which, as a practical philosophy, has special importance in applied research. The present study is descriptive in terms of its purpose and cross-sectional in terms of time horizon. Additionally, in terms of orientation, it is considered as an applied research study. The research approach is mixed (qualitative-quantitative) and has been conducted in two stages. In the first stage, with a qualitative approach, through conducting a systematic literature review and semi-structured interviews with experts, the technologies and applications of Industry 4.0 in maritime industries were identified. In the second stage, with a quantitative approach, the Best-Worst Multi-Criteria Decision-Making method was used to rank and determine the relative importance of each technology and its application.

The statistical population of the study includes specialists and experts in the country's maritime industries. Sampling was done using a purposeful method and 15 experts including 12 middle managers of maritime industries and 3 university professors who work as consultants in this industry were selected. The criterion for selecting the experts was having at least 6 years of experience in maritime industries and familiarity with the concepts and applications of Industry 4.0.

In the qualitative stage, a systematic literature review was conducted to extract articles related to Industry 4.0 technologies in maritime industries, identifying 59 applications. These applications were statistically validated using a T-test to confirm their relevance to maritime industries, retaining only those with statistical significance ($p < 0.05$). Following the literature review and statistical validation, semi-structured interviews were conducted with experts. An interview protocol was used to guide the interviews, and interviewees were asked to validate and assess the applications of Industry 4.0 identified from the literature. To ensure the reliability of the analysis, the interview data was reviewed by two independent researchers, and an agreement coefficient of over 70 percent was obtained, indicating appropriate reliability.

In the quantitative stage, the Best-Worst Multi-Criteria Decision-Making method was used to rank and determine the relative importance of tools and applications. This method requires fewer pairwise comparisons compared to other multi-criteria decision-making methods such as AHP, and its results have higher reliability (Rezaei, 2016). The number of pairwise comparisons required in this method is calculated from the formula 2*m-3.

The steps of this method are as follows:

Step One: In this step, a set of decision-making indicators, which includes 59 tools and applications of Industry 4.0 in maritime industries, was determined.

Step Two: In this step, based on the expert opinion, the best and worst criteria among the factors were determined.

Step Three: The preference of the best indicator relative to other indicators is done on a scale of 1 to 9, which is shown as a preference vector in the form of $A_B = (a_{b_1}, a_{b_2}, \ldots, a_{b_n})$. In the mentioned vector, a_{b_j} represents the preference of the best criterion (b) over criterion (j), and it is clear that $a_{bb} = 1$.

Step Four: The preference of all indicators relative to the worst option is specified on a scale of 1 to 9. The preference vector of other indicators to the worst indicator is represented as $A_W = (a_{1W}, a_{2W}, ..., a_{nW})$. a_{jw} represents the preference of indicator (j) over the worst indicator (w), and it is clear that $a_{WW} = 1$.

Step Five: In this step, since the questionnaire has been distributed among 15 people, it is necessary to take an average, and subsequent calculations were performed on this average.

Step Six: The optimal weight values were determined. Thus, the model can be formulated as follows:

$$\begin{aligned}
&\min max_j \left(\left|\frac{WB}{Wj} - a_{Bj}\right|, \left|\frac{wj}{Ww} - a_{jw}\right|\right) \\
&\text{s.t.} \\
&\sum_j wj = 1 \\
&wj \geq 0 \; for \; all \; j
\end{aligned} \tag{1}$$

Furthermore, the above model can be converted to the following model:

$$\begin{aligned}
&\min \;\; \xi \\
&s.t. \\
&\left|\frac{WB}{Wj} - a_{Bj}\right| \leq \xi, \text{for all j} \\
&\left|\frac{wj}{Ww} - a_{jw}\right| \leq \xi, \text{for all j} \\
&\sum_j^w wj = 1 \\
&wj \geq 0 \; for \; all \; j
\end{aligned} \tag{2}$$

The linear function model is presented as follows (Rezaei, 2016) and is also used in this article:

$$\begin{aligned}
&\min \;\; \xi \\
&s.t. \\
&\left|w_B - a_{Bj} w_j\right| \leq \boldsymbol{\xi}, \text{for all } j \\
&\left|w_j - a_{jw} w_w\right| \leq \boldsymbol{\xi}, \text{for all } j \\
&\sum_j^w wj = 1 \\
&wj \geq 0 \; for \; all \; j
\end{aligned} \tag{3}$$

Finally, by solving the above model, the optimal weight values and inconsistency rate were obtained.

Findings

Through conducting a systematic literature review (as summarized in Table 1), we identified emerging technologies of Industry 4.0 and their applications in maritime industries. This review yielded 12 key technology categories and their potential applications. To validate these findings and enrich the framework, the interviews were conducted with 12 middle managers of maritime businesses and 3 academic experts who worked as consultants in these fields. The expert consultation confirmed the relevance of 12 technologies identified from the literature and validated 59 specific applications of these technologies in maritime contexts.

The technologies identified through systematic literature review and validated by experts were categorized as follows: Internet of Things (IoT), Blockchain, AI and Machine Learning, Robotics and Automation, Augmented Reality, 3D Printing, Cloud Computing, Smart Asset Management, Cybersecurity, Environmental Monitoring, Big Data Analytics, and Digital Twin Systems.

Initially, the main technologies and their applications were identified and categorized. The results of the T-test are presented in Table 2. Accordingly, the final framework based on the main technologies and their related applications is as follows:

Internet of Things (IoT): By examining the concepts obtained from the analysis of the interviews, the first key technology was the Internet of Things. This technology provides the possibility of real-time data collection and intelligent monitoring by creating integrated networks of sensors and connected equipment. Based on the interviews, its most important applications include tracking and locating containers, monitoring port equipment, managing ship traffic, and collecting environmental data. For example, one expert stated: *"IoT provides real-time monitoring of equipment and container conditions, which is essential for optimizing port operations".*

Blockchain: The second key technology identified was blockchain, which provides the capability for transparency and traceability in transactions. According to experts, the most important applications of this technology include increasing transparency in the supply chain, facilitating information exchange between stakeholders, reducing intermediary intervention, and increasing security in transactions. One expert stated: *"Blockchain, by eliminating intermediaries and creating transparency, can transform business processes in the maritime industry".*

Artificial intelligence (AI): The third important technology is AI and machine learning. This technology plays an important role in operations optimization with its ability to analyze complex data and learn from patterns. The most important identified applications include real-time ship arrival prediction (enabling precise scheduling through advanced algorithms), analyzing maritime traffic risks, predictive fuel optimization using AI algorithms (reducing fuel use by up to 15% through real-time predictive models), and managing intelligent terminals. According to one specialist: *"Artificial intelligence, with accurate prediction of ship arrival times, provides the possibility for optimal operations planning".*

Robotics and Automation: This technology plays an important role in increasing productivity and safety with the aim of automating operations. Its main applications include automatic guidance of vehicles in the port area, preventive monitoring and maintenance of equipment, automation of operational processes, and development of automated cranes. Experts believe: *"Port automation, in addition to increasing productivity, helps reduce human error and increase safety".*

Augmented Reality: Studies show that augmented reality, with the ability to combine the real and virtual worlds, has various applications in maritime industries. The most important applications identified for this technology include employee training, assistance in ship berthing operations, equipment inspection and maintenance, and digitization of inspection processes. One expert noted: "*Augmented reality provides the possibility for practical and interactive training for employees, which is much more effective than traditional methods".*

3D Printing: This technology has created a transformation in maintenance and repairs with the possibility of custom production of parts. Based on the interviews, its main applications include producing spare parts of the ship, manufacturing ship molds, repairing and rebuilding parts, rapid prototyping, and localizing parts production. Experts believe: *"3D printing can significantly reduce the time and cost of supplying spare parts".*

Cloud Computing: This technology provides the necessary software infrastructure for data processing and storage. Its main applications include data sharing between stakeholders, managing port information, networking for design and production, and planning joint operations. One specialist stated: "Cloud Computing provides the possibility of integrated access to data and effective collaboration between stakeholders".

Smart Asset Management: The eighth identified technology is Smart Asset Management, which plays an important role in optimizing the performance of equipment. The main applications of this technology include monitoring the condition of port infrastructure, predicting repairs, reducing maintenance costs, and improving the life cycle of ships. One expert emphasized: *"Smart asset management prevents unwanted stoppages by timely predicting maintenance needs".*

Cybersecurity: In the digital age, cybersecurity has become one of the most essential technologies. Based on the interviews, its most important applications are protecting information systems, managing cyber risks, protecting vital infrastructure, and reducing risk, and increasing safety. According to specialists: *"With increased system connectivity, cybersecurity has become a strategic priority".*

Environmental Monitoring: This technology has been developed with the aim of monitoring and reducing environmental impacts. Its main applications include monitoring environmental conditions, reducing carbon emissions, monitoring hazardous material leaks, and identifying and reducing energy waste. Experts believe: *"Environmental monitoring plays a key role in achieving sustainability goals and reducing pollution".*

Big Data Analytics: Change to: The eleventh identified technology is big data analytics, which provides the possibility of extracting insights from massive volumes of data. Its most important applications include historical ship arrival trend analysis (identifying patterns in past arrival data), analyzing maritime traffic risks, fuel efficiency analysis using historical data (leveraging large datasets to identify fuel-saving opportunities), controlling ship performance, preventive maintenance, and data-based decision-making. One specialist stated: *"Big data analytics provides the possibility for more accurate and faster decision-making".*

Digital Twin Systems: Change to: The last and most important identified technology is Digital Twin Systems, which provide the possibility of accurate simulation of physical systems in the digital world. The main applications of this technology include ship performance simulation for operational scenarios (e.g., optimizing navigation or cargo handling), ship performance simulation for design validation (e.g., testing ship designs before construction), training employees with virtual models, optimizing operations by testing different scenarios and predicting maintenance needs. According to one expert: *"Digital Twin Systems, with accurate simulation of operations, provide the possibility of process optimization without the risks of the real world"* (see Table 2).

Table 2.
T-test

Tools	Applications	Mean	Standard Deviation	t	Sig.
Internet of Things (IoT)	Container tracking and locating	3.80	1.014	3.055**	0.009
	Port equipment monitoring	4.13	0.834	5.264**	0.000
	Ship traffic management	3.87	0.834	4.026**	0.001
	Environmental and oceanography data collection	3.93	0.884	4.090**	0.001
	Controlling and monitoring of port facilities	3.40	0.507	3.055**	0.009
	Decision-making using automatic data	3.93	0.884	4.090**	0.001
Blockchain	Increasing transparency in supply chain	4.67	0.488	13.229**	0.000
	Facilitating information exchange between stakeholders	4.53	0.640	9.280**	0.000
	Reducing intermediary intervention	4.13	0.834	5.264**	0.000
	Enhanced security in transactions	3.87	0.834	4.026**	0.001
	Information management between stakeholders	3.60	1.056	2.201**	0.045
Artificial Intelligence and Machine Learning	Real-time ship arrival prediction	4.27	0.799	6.141**	0.000
	Maritime traffic risk analysis	4.00	1.000	3.873**	0.002
	Predictive fuel optimization using AI algorithms	4.67	0.617	10.458**	0.000
	Intelligent terminal management	4.33	0.816	6.325**	0.000
Robotics and Automation	Automatic control of port cranes	3.07	1.163	0.222	0.827
	Automatic guidance of vehicles in port area	4.60	0.632	9.798**	0.000
	Preventive monitoring and maintenance of equipment	3.93	0.884	4.090**	0.001
	Automation of operational processes	4.20	0.775	6.00**	0.000
	Development of automated access bridges	4.07	0.799	5.172**	0.000
	Improving operations with autonomous ships	4.47	0.640	8.876**	0.000
Augmented Reality	Employee training	4.67	0.617	10.458**	0.000
	Assistance in ship berthing operations	3.80	1.014	3.055**	0.009
	Equipment inspection and maintenance	4.60	0.632	9.798**	0.000
	Digitization of inspection processes	4.33	0.816	6.325**	0.000
3D Printing	Production of spare parts of the ships	3.07	1.335	0.193	0.849
	Manufacturing ship molds	4.40	0.910	5.957**	0.000
	Repair and rebuilding of parts	4.47	0.640	8.876**	0.000
	Rapid prototyping with reduced time and cost	4.53	0.640	9.280**	0.000
	Localization of parts production	4.47	0.640	8.876**	0.000
Cloud Computing	Data sharing between stakeholders	3.20	0.414	1.871	0.082
	Port information management	4.33	0.816	6.325**	0.000
	Networking for design and production	4.67	0.617	10.458**	0.000

Tools	Applications	Mean	Standard Deviation	t	Sig.
	Planning of joint operations	3.80	1.014	3.055**	0.009
	Collaboration between shipping lines and terminals	3.87	0.834	4.026**	0.001
Smart Asset Management	Monitoring the condition of port infrastructure	4.00	1.000	3.873**	0.002
	Predicting repairs	4.27	0.799	6.141**	0.000
	Reducing maintenance costs	4.47	0.640	8.876**	0.000
	Improving ship life cycle	4.33	0.816	6.325**	0.000
Cyber-security	Protection of information systems	3.93	0.884	4.090**	0.001
	Managing cyber risks	4.67	0.617	10.458**	0.000
	Protection of vital infrastructure	4.47	0.640	8.876**	0.000
	Risk reduction and safety improvement	4.60	0.632	9.798**	0.000
Environmental Monitoring	Monitoring environmental conditions	3.27	0.458	2.256**	0.041
	Reducing carbon emissions	4.47	0.640	8.876**	0.000
	Using low-carbon fuels	3.13	1.457	0.354	0.728
	Monitoring hazardous material leaks	4.60	0.632	9.798**	0.000
	Identifying and reducing energy waste	4.27	0.799	6.141**	0.000
Big Data Analytics	Historical ship arrival trend analysis	3.07	1.335	0.193	0.849
	Analyzing maritime traffic risk	3.67	1.047	2.467**	0.027
	Fuel efficiency analysis using historical data	4.53	0.640	9.280**	0.000
	Controlling the ship performance	4.27	0.799	6.141**	0.000
	Preventive maintenance	4.47	0.640	8.876**	0.000
	Data-based decision-making	4.60	0.632	9.798**	0.000
Digital Twin Systems	Ship performance simulation for operational scenarios	4.53	0.640	9.280**	0.000
	Employee training with virtual models	4.67	0.617	10.458**	0.000
	Operations optimization by testing different scenarios	4.73	0.458	14.666**	0.000
	Predicting maintenance needs	4.53	0.640	9.280**	0.000
	Ship performance simulation for design validation	4.47	0.516	11.00**	0.000

** Significant at 0.05 level

(Source: Researcher's Findings)

Change to: Based on the results of statistical analysis in Table 2, out of the total 59 identified applications, 5 applications were eliminated due to lack of statistical significance ($p>0.05$): 'Automatic control of port cranes' (t=0.222, Sig.=0.827), 'Use of low-carbon fuels' (t=0.354, Sig.=0.728), 'Historical ship arrival trend analysis' (t=0.193, Sig.=0.849), 'Production of spare parts of the ships' (t=0.193, Sig.=0.849), and 'Data sharing between stakeholders' (t=1.871, Sig.=0.082). The remaining 54 applications proceeded to the next stage. In the next stage, the Best-Worst method was used to determine the relative importance and weight of each technology and its related applications. First, the weight of the applications for each technology was determined and then compared with each other. The final weight of the applications was calculated from the product of the two obtained weights. Additionally, the inconsistency rate for all weights was calculated and confirmed. The results are shown in Table 3.

Table 3.
The Ranking of Applications

Tools	Tool Weight	Applications	Application Weight	Final Weight	Rank
Internet of Things (IoT)	4.83	Container tracking and locating	9.80	47.334	44
		Monitoring Port equipment	32.68	143.4652	22
		Ship traffic management	13.07	157.8856	19
		Environmental and oceanography data collection	19.61	315.9171	9
		Controlling and monitoring port facilities	5.23	36.087	47
		Decision-making using automatic data	19.61	105.3057	29

Tools	Tool Weight	Applications	Application Weight	Final Weight	Rank
Blockchain	4.39	Increasing transparency in supply chain	40.37	177.2243	17
		Facilitating information exchange between stakeholders	24.60	297.168	10
		Reducing intermediary interventions	16.40	264.204	11
		Enhanced security in transactions	12.30	84.87	33
		Information management between stakeholders	6.30	33.831	48
Artificial Intelligence and Machine Learning	12.08	Real-time ship arrival prediction	17.24	208.2592	16
		Maritime traffic risk analysis	10.34	166.5774	18
		Predictive fuel optimization using AI algorithms	46.55	321.195	8
		Intelligent terminal management	25.86	138.8682	23
Robotics and Automation	16.11	Automatic guidance of vehicles in port area	41.61	670.3371	2
		Preventive monitoring and maintenance of equipment	5.78	39.882	46
		Automation of operational processes	16.18	86.8866	32
		Development of automated access bridges	12.13	48.7626	43
		Improving operations with autonomous ships	24.27	73.7808	34
Augmented Reality	6.90	Employee training	48.46	334.374	6
		Assistance in ship berthing operations	9.23	49.5651	42
		Equipment inspection and maintenance	25.38	102.0276	30
		Digitization of inspection processes	16.92	51.4368	41
3D Printing	5.37	Manufacturing ship molds	10.34	55.5258	40
		Repairing and rebuilding parts	17.24	92.5788	31
		Rapid prototyping with reduced time and cost	46.55	249.9735	12
		Localization of parts production	25.86	138.8682	23
Cloud Computing	4.02	Port information management	0.30	1.203	52
		Networking design and production	0.51	2.0502	51
		Planning joint operations	0.07	0.2814	54
		Collaboration between shipping lines and terminals	0.12	0.4824	53
Smart Asset Management	3.04	Monitoring the condition of port infrastructure	9.52	28.9407	49
		Predicting repairs	23.80	72.352	35
		Reducing maintenance costs	42.85	130.264	25
		Improving ship life cycle	23.80	72.352	35
Cyber-security	8.05	Protecting the information systems	8.13	65.4465	38
		Managing cyber risks	47.15	379.5575	5
		Protecting vital infrastructure	17.88	143.934	21
		Risk reduction and safety improvement	26.82	215.901	15
Environmental Monitoring	2.44	Monitoring environmental conditions	6.57	16.0308	50
		Reducing carbon emissions	27.63	67.4172	37
		Monitoring hazardous material leaks	47.36	115.5584	28
		Identifying and reducing energy waste	18.42	44.9448	45
Big Data Analytics	9.67	Analyzing maritime traffic risks	5.78	55.8926	39
		Fuel efficiency analysis using historical data	24.27	234.6909	14
		Controlling the ship performance	12.13	117.2971	27
		Preventive maintenance	16.18	156.4606	20
		Data-based decision-making	41.61	402.3687	4
Digital Twin Systems	20.02	Ship performance simulation for operational scenarios	16.40	328.328	7
		Employee training with virtual models	24.60	492.492	3
		Optimizing operations by testing different scenarios	40.38	808.4076	1
		Predicting maintenance needs	12.30	246.246	13
		Ship performance simulation for design validation	6.30	126.126	26

(Source: Researcher's Findings)

Based on the results in Table 3, Digital Twin Systems with a weight of 20.2 is the most important technology (tool) of the Fourth Industrial Revolution in maritime industries. The next technologies in order are Robotics and Automation with a weight of 16.11, Artificial Intelligence and Machine Learning with a weight of 12.08, and finally Environmental Monitoring with a weight of 2.44. Overall, the top-ranked application belongs to Optimizing Operations by Testing Different Scenarios in Digital Twin Systems technology. Additionally, the application of Automatic Guidance of Vehicles in Port Area in Robotics and Automation technology and Employee Training with Virtual Models in Digital Twin Systems technology ranked as the second and third, respectively. Planning Joint Operations and Collaboration between Shipping Lines and Terminals occupied the last two positions.

Discussion and Conclusion

Discussion

The maritime industry in the present era has different conditions. Some specialists in this industry consider the current environment as turbulent and full of continuous changes, where success requires new and up-to-date technologies (Ilias et al., 2023). This aligns with the concept of a VUCA (Volatility, Uncertainty, Complexity, and Ambiguity) environment, where leadership and decision-making require specific cognitive skills and strategic approaches to navigate effectively through uncertainties (Hafezniya & Ansari, 2024). The emergence of advanced Industry 4.0 technologies, along with increasing competitive pressures, stringent environmental requirements, the need to reduce fuel consumption, and the necessity to enhance operational safety, has caused maritime industries to be in a state of high change both in terms of internal processes and macro-environmental forces (Ilias et al., 2023). The importance of applying emerging technologies in various transportation sectors, including intelligent transportation, has also been emphasized by Fasanghari and Asarian (2024). They found that the fifth-generation technologies can lead to significant improvements in efficiency and safety of transportation systems.

Additionally, the experience of leading global ports shows that implementing these technologies can lead to a 15 to 20 percent increase in operational productivity and a 30 percent reduction in maintenance costs (Ilias et al., 2023).

Based on studies and interviews conducted with industry experts, out of a total of 59 applications identified in the form of 12 key technologies, 54 applications were selected for final analysis and ranking. The results of the statistical analysis showed that Digital Twin Systems with a weight of 20.02 is the most important technology of the Fourth Industrial Revolution in maritime industries, followed by Robotics and Automation with a weight of 16.11, and Artificial Intelligence and Machine Learning with a weight of 12.08.

The analysis of the prioritization results reveals several significant patterns. First, there is a clear preference for technologies that enable operational simulation and automation, with Digital Twin Systems (20.02) and Robotics and Automation (16.11) receiving the highest weights. This suggests that maritime industry stakeholders prioritize technologies that can reduce the operational risk while increasing the efficiency. Second, the highest-ranked applications tend to focus on three core areas of operations optimization (particularly through scenario testing), workforce enhancement (through training and automation), and safety improvement. This pattern indicates that Industry 4.0 adoption in maritime industries is driven by a balanced consideration of the operational efficiency, human factors, and risk management (Zarei & Naderi, 2024). Third, the relatively lower ranking of infrastructure technologies like IoT (4.83) and Cloud Computing (4.02) may indicate that these are increasingly viewed as fundamental enablers rather than strategic differentiators. This finding aligns with the technology adoption lifecycle model, where certain technologies transition from competitive advantages to necessary conditions for operation.

In examining the applications of Industry 4.0 technologies, Operations Optimization by Testing Different Scenarios ranked first. This finding is consistent with the results of Yang et al.'s (2018) study, which showed that simulation and optimization of processes before implementation can reduce design time by up to 50 percent. Additionally, Automatic Guidance of Vehicles in Port Area and Employee Training with Virtual Models ranked as the second and third. This prioritization shows that the maritime industry is moving toward the operation automation and the development of human resource skills.

Big Data Analytics with a weight of 9.67 was identified as the fourth most important technology, indicating the growing importance of data-driven decision-making in maritime industries. Among the applications of this technology, Data-Based Decision-Making with a final weight of 402.3687 ranked fourth, demonstrating the vital role of data analysis in optimizing the operations.

Cyber-security with a weight of 8.05 ranked fifth, indicating that with increased system connectivity and digitization of operations, the protection of vital infrastructure has become an important priority. Additionally, it was found that infrastructure technologies such as Internet of Things with a weight of 4.83 and Cloud Computing with a weight of 4.02 are in lower ranks, which could indicate the relative maturity of these technologies in industry.

Implementation Challenges of Industry 4.0 Technologies

While the prioritization of Industry 4.0 technologies offers a strategic guide for maritime industries, their implementation is not without challenges. High initial investment costs, often reaching hundreds of millions of dollars for technologies like Digital Twin Systems or port automation, pose significant financial barriers, particularly for smaller organizations (Vanelslander et al., 2019). Technical complexities, such as integrating new systems with legacy infrastructure, further complicate the adoption, requiring substantial expertise and time (Boyes et al., 2016). Regulatory constraints, including compliance with international maritime standards and environmental regulations, add another layer of difficulty, as organizations must navigate complex approval processes (Acciaro et al., 2018). Additionally, the increased connectivity inherent in technologies like IoT and Cloud Computing raises cyber-security risks, necessitating robust protection measures to safeguard critical infrastructure (Kim, 2017). Workforce training is also a critical barrier, as employees must acquire new skills to operate advanced systems, which can strain organizational resources (Chu et al., 2018). These challenges highlight the need for careful planning and resource allocation to ensure successful technology adoption. Addressing these barriers through phased implementation, public-private partnerships, or targeted training programs could facilitate smoother integration of Industry 4.0 technologies in maritime industries.

Case Examples Supporting Prioritization

To validate the prioritization of Industry 4.0 technologies, real-world applications at leading ports provide illustrative evidence. The Port of Rotterdam, a pioneer in Digital Twin Systems, implemented a digital twin for terminal operations, resulting in a reported 25% increase in the operational productivity by optimizing resource allocation and reducing vessel turnaround times (PTI, 2019). The initial investment was substantial, estimated at €50 million, but the long-term savings in operational costs justified the expenditure. Similarly, the Port of Singapore adopted Robotics and Automation for container handling, achieving a 20% reduction in loading and unloading times through using automated guided vehicles and smart cranes (Woo, 2018). While the upfront costs for automation infrastructure were high, the port reported a 15% decrease in labor costs and improved safety outcomes. These cases align with our findings, where Digital Twin Systems (weight: 20.02) and Robotics and Automation (weight: 16.11) ranked the highest, demonstrating their transformative potential. Although comprehensive cost-benefit analyses require detailed financial data beyond this study's scope, these examples underscore the practical value of prioritizing high-impact technologies in maritime industries.

Conclusion

A review of previous research shows that despite the existence of extensive studies in the field of Industry 4.0 and its applications in maritime industries, there has been a significant gap in prioritizing and selecting these technologies; therefore, this research study attempted to help fill this research gap by providing a systematic framework for evaluating and prioritizing Industry 4.0 technologies. Asarian et al. (2025) showed that strategic flexibility and alignment of information technology strategy with organizational goals play a key role in improving the business performance in dynamic and changing environments. This is particularly important in maritime industries that face numerous challenges in adapting to emerging technologies. The results of this study can help managers and decision-makers in maritime industries to select and implement appropriate technologies and provide guidance for optimal resource allocation and reduction of investment risks.

Recommendations for Organizations at Different Digital Maturity Levels

To maximize the benefits of Industry 4.0 technologies, maritime organizations should adopt strategies aligned with their level of digital maturity. For beginner organizations, which may lack advanced infrastructure, we recommend starting with foundational technologies like IoT for equipment monitoring or Cloud Computing for data sharing. These technologies require moderate investment and provide immediate operational insights, building a base for further digitalization (Yang et al., 2018). Intermediate organizations, with some digital capabilities, should focus on integrating high-impact technologies like Robotics and Automation for port operations or Big Data Analytics for decision-making. These organizations can leverage the existing systems to scale up efficiency while investing in workforce training to support adoption (Chu et al., 2018). Advanced organizations, already equipped with sophisticated systems, should prioritize cutting-edge technologies like Digital Twin Systems for scenario testing or Cyber-security to protect the integrated networks. These organizations can also lead industry-wide initiatives, such as developing shared digital platforms or piloting Blockchain for supply chain transparency (Li, 2018). Tailoring technology adoption to digital maturity ensures the optimal resource use and minimizes the implementation risks, enabling organizations to progressively enhance their competitiveness and sustainability.

Limitations and Future Research Directions

This study has several limitations that should be acknowledged. First, the research was conducted with a limited sample of experts from one country, which may affect the generalizability of the findings to other geographical contexts with different technological adoption rates and maritime industry characteristics. Second, the rapid pace of technological advancement means that new technologies may emerge and change the priority landscape in a relatively short time frame. While this study now includes a discussion of implementation challenges—such as financial, technical, regulatory, and human resource barriers—a comprehensive analysis of these factors was beyond its scope, leaving room for future studies to investigate overcoming these barriers through implementing approaches like case studies or cost-benefit analyses.

The study focused primarily on the prioritization of technologies without deeply exploring the implementation challenges, cost-benefit analysis, or the interdependencies between different technologies. The barriers to adoption, including financial constraints, regulatory issues, and workforce readiness, were not extensively examined. To address the organizational diversity, this study provides tailored recommendations for different digital maturity levels, though these are based on broad categorizations of beginner, intermediate, and advanced stages. Future research could refine these into more granular frameworks by considering specific contexts such as organization size, sector, or regional differences.

For future research, it is suggested to investigate the mutual impact of different technologies on each other and the role of contextual factors such as organization size, digital maturity, and organizational culture in the successful implementation of these technologies. Longitudinal studies tracking the implementation process and the outcomes of these technologies would provide valuable insights into their real-world effectiveness and challenges.

Further research could also explore the development of more detailed implementation roadmaps for maritime organizations at different stages of technological maturity, as well as conducting comparative analyses across different countries and maritime sectors. Finally, future studies should consider the sustainability implications of Industry 4.0 technologies in maritime industries, examining how these technologies can contribute to environmental goals while improving operational efficiency.

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Application of Artificial Intelligence in Predicting and Managing Financial Distress: A Case Study of Listed Companies in Iran

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ABSTRACT

Financial distress analysis is one of the essential and important topics in financial management, playing a vital role for investors, creditors, and other users of financial information. Predicting the likelihood of financial distress in companies before it occurs can provide valuable opportunities for managers in terms of risk management, as well as for investors and creditors in making better decisions. In this research, using data from manufacturing companies listed in Tehran Stock Exchange from 2011 to 2018 that have faced financial distress, the factors influencing financial distress were identified and, its prediction was examined using advanced Artificial Intelligence (AI) algorithms, including system dynamics and fuzzy logic. The results indicated that key variables such as production and demand played a decisive role in the occurrence of financial distress. These findings not only provided a tool for more accurate predictions of financial distress but also offered a framework for preventive policymaking in companies.

KEYWORDS

Artificial Intelligence (AI), Financial Distress, Fuzzy Logic, System Dynamics.

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Introduction

Since the 1950s, with the increase in the number of companies and business institutions and the complexity of economic and commercial relationships, the tasks of financial management have undergone significant changes. Governments' emphasis on economic growth has further contributed to the increase in the number of companies and institutions, making these tasks even more complex (Komeijani & Saadatfar, 2006). On the other hand, human access to new communication and information technologies has brought about environmental changes, which have accelerated the processes in the economy. The acceleration of activities and economic events has led to both positive and negative consequences. From among the most important negative outcomes, the most challenging ones are the intensification of competition for acquiring financial resources and the restricted access to profit by business units and economic enterprises. The limitation of access to profits and financial resources results in various consequences, the most significant of which is the increased probability of financial distress and bankruptcy in businesses and commercial units (Altman, 1968).

Bankruptcy of companies has always been one of the main concerns of investors, creditors, and governments. Timely identification of companies that are on the verge of bankruptcy can significantly reduce potential losses for stakeholders. The development of bankruptcy prediction models has always been a major topic of interest for both the academic community and economic enterprises (Moshaiehi & Ganji, 2014).

To appropriately seize investment opportunities and prevent resource wastage, one effective approach is to predict financial distress or bankruptcy. This can be achieved by first providing early warnings to companies about potential distress so that they can take necessary actions in response, and second, enabling investors to distinguish between favorable and unfavorable investment opportunities and allocate their resources accordingly. Predicting financial distress in companies has long been a significant topic in the fields of finance and economics. Therefore, this paper analyzes financial distress in production sector, emphasizing the role of macroeconomic, financial, managerial, and risk variables using AI algorithms.

Literature Review

Theoretical Foundations

Financial distress in banks, public, and private companies is a serious issue for the economic survival of countries. The individual and societal costs of financial distress have made predicting financial distress an important issue for many managers, banks, investors, policymakers, and auditors. Predicting financial distress is of significant importance to three groups of managers, creditors, and auditors. Managers, as agents of shareholders, must be proactive in activities that ensure the continuity and profitability of the company. Creditors, in evaluating a company's ability to repay its obligations, are interested in assessing the continuity of the business. Auditors, as another group, must express their opinion regarding the continuity of the company's operations and the fairness of the financial information in reports. Therefore, they are interested in predicting financial distress or the continuity of a company's operations (Khoshtinat et al., 2005).

Given the development of companies, increased economic activities, heightened competition, and cycles of inflation and recession in recent decades, the number of companies experiencing financial distress and the significance of such distress have been increasing. The issue of bankruptcy and financial distress has always been a topic of concern. Therefore, studying the causes of financial distress and assessing the existing models is of high importance (Ahmadpour & Shahsavari, 2014).

Financial distress and bankruptcy of companies result in wasted resources and the inability to capitalize on investment opportunities. Predicting financial distress through the design of appropriate indicators and models can alert companies to the potential occurrence of financial distress and bankruptcy, allowing them to adopt appropriate policies in response to these warnings. On the other hand, market participants in both the capital and money markets need awareness and knowledge about the financial status and efficiency of the existing companies. One of the methods that can help ensure the efficient use of investment opportunities and better allocation of resources is the prediction of financial distress or bankruptcy. By providing the necessary warnings, companies can be alerted to potential financial distress, prompting them to take corrective actions. Additionally, investors and creditors can distinguish between desirable and undesirable investment opportunities and direct their resources towards the more favorable ones (Mehrani et al., 2004). Therefore, the prediction of financial distress and bankruptcy has always been a major subject for investors, creditors, and governments. Timely identification of companies nearing financial distress is highly desirable because it prevents investments in unproductive and inefficient opportunities for market participants.

From an economic perspective, financial distress can be interpreted as the company being in a loss-making position, meaning the company has failed to succeed. In this case, the company's return rate is lower than its cost of capital. Another form of financial distress occurs when a company fails to comply with one or more clauses in its debt agreements, such as maintaining the current ratio or the equity-to-total-assets ratio as stipulated in the contract. This situation is referred to as technical default. Other forms of financial distress include when the company's cash flows are insufficient to meet both principal and interest payments on debt or when the company's equity becomes negative (Weston et al., 1992).

Today, investors have a wide range of options when selecting areas for investment. Therefore, decision-making for investors is becoming increasingly complex and risky. The outcomes of these investments can have significant impacts on people's lives. Bankruptcy is an event that can challenge a country both socially and economically.

In this regard, changes in financial status of the companies serve as a useful guide for investors in making subsequent decisions (Altman, 1968). Financial distress and ultimately the bankruptcy of economic units can result in significant losses at both the micro and macro levels.

At the macro level, financial distress in companies causes:

1. A reduction in GDP
2. An increase in unemployment
3. The waste of national resources and similar consequences.

At the micro level, it leads to substantial losses for stakeholders and economic entities such as shareholders, potential investors, creditors, managers, employees, suppliers, and customers. Therefore, to avoid the massive losses that arise from financial distress, it is necessary to conduct studies in this field. Thus, finding models to predict financial distress that occurs before bankruptcy is of great importance (Esmailzadeh Maghari & Shakeri, 2015).

One of the ways to effectively utilize investment opportunities and allocate resources better is by evaluating financial distress. Through financial distress evaluation, the financial situation of companies is clarified, and their distress is examined so that shareholders and managers can take measures to prevent distress or make changes to the company's structure. By taking the right and timely actions, they can potentially prevent the company from heading toward bankruptcy.

Therefore, evaluating the financial distress of companies has always been a topic of interest for investors, creditors, and governments. Timely identification of companies that are on the verge of financial distress is highly desirable (Rostami et al., 2011).

With the increasing expansion of joint-stock companies and the emergence of severe financial crises at both the micro and macroeconomic levels, owners and stakeholders of businesses have sought to create protection against such risks. This has made them more sensitive and aware of using appropriate predictive models to evaluate the financial capability of companies (Kurdistani et al., 2011).

One of the most important pieces of information that can assist economic decision-makers in making optimal resource allocation decisions is identifying the variables for predicting bankruptcy and financial distress in companies. Therefore, finding financial warning indicators has always been one of the most popular areas of research in the field of finance.

Financial distress in a company is usually determined by various interconnected factors; hence, accurately identifying the causes of financial distress in each case is not always easy. Generally, the factors of financial distress include both external and internal factors. External factors are those that cannot be controlled by the company but create financial problems for it. These include changes in economic structures, business fluctuations (such as mismatches between production and consumption, sales decline, inflation, price drops, and rising interest rates), issues related to financing, natural disasters, and increased competition. Internal factors include instances where managers have made mistakes or failed to take necessary actions in past management decisions. Examples include excessive credit sales, poor management (lack of training, experience, ability, and innovation in management, competition, technology, resources, and management errors), inability to effectively manage capital, fraud, and embezzlement (Komeijani & Sadatfar, 2006).

The most important reasons for bankruptcy in Iran can be attributed to economic fluctuations as an external factor and higher production costs, interest expenses, and the improper determination of capital structure as internal factors. Liquidity problems are considered one of the major factors affecting the financial crises of companies (Weston et al., 1992).

Decision-making in financial matters has always been associated with risk and uncertainty. One way to assist investors is to provide predictive models about the overall outlook of a company.

The closer the predictions are to reality, the more reliable and complete the basis for making decisions will be. Beaver states, "prediction can be made without decision-making, but no decision, however small, can be made without prediction" (Mehrani et al., 2005).

Numerous efforts have been made to develop predictive models for the overall outlook of companies, particularly in the area of financial distress and bankruptcy. The result of these efforts has been the creation of various models that now accurately predict the likelihood of such events.

Studies show that although statistical models have been able to provide good predictions regarding financial distress or bankruptcy in companies, some of the restrictive assumptions of these models, such as linearity, normality, and the independence of the predicting variables, have affected the effectiveness of these methods. Therefore, over time, other methods have been introduced to overcome some or all of these limitations and improve prediction performance. For example, artificial neural networks, genetic algorithms, and support vector machines can be mentioned (Raaei & Fallahpour, 2008).

Research Background

Numerous studies have been conducted regarding the ability of financial statements to predict financial distress. Some of the most important and relevant studies to this research are outlined below:

In 1942, Charles Merwin conducted a study in which he examined financial ratios for bankrupt and non-bankrupt companies over a six-year period. He stated that the ratios of working capital to total assets, equity to total liabilities, and the current ratio were good predictors of bankruptcy. Merwin concluded that the ratio of working capital to total assets was the best indicator of the bankruptcy (Horrigan, 1968).

The first person to use univariate analysis for predicting financial distress in companies was Beaver. He selected 79 bankrupt and 79 non-bankrupt companies and, out of 30 financial ratios, identified 6 with the lowest error rates, such as the ratio of cash flow to total assets, the ratio of net profit to total assets, the ratio of total liabilities to total assets, the ratio of working capital to total assets, current ratio, and the uncertainty ratio. Beaver's findings showed that the ratio of cash flow to total debt had the highest predictive power (Beaver, 1966).

Edward Altman, in 1968, for the first time examined the effect of various financial ratios in predicting financial distress in companies. Altman used Multiple Discriminant Analysis (MDA) in his study. The model he developed, known as the Z-Score, is still widely used as an indicator of a company's financial health. Altman's theory was that his bankruptcy prediction model, which consists of 5 financial ratios, could distinguish between bankrupt and non-bankrupt companies. He suggested that his model could be used for evaluating business loans, internal control processes, and investment options (Altman, 1968).

Elson (1980) developed a model using logistic regression and data from 105 bankrupt and 205 non-bankrupt companies from 1970 to 1976. He incorporated 9 financial ratios as independent variables, 5 of which had been used in previous studies (Elson, 1980).

Another study used financial ratios based on cash flow statements and balance sheets to identify bankrupt companies. The study, which covered a 5-year period and used data from 60 bankrupt and 230 non-bankrupt companies, concluded that cash flow ratios were more effective than balance sheet and profit-loss ratios in predicting financial distress (Kazi, 1984).

Wallace used artificial neural networks to design his model. The 5 financial ratios used in his model included: working capital to total assets, cash flows to total liabilities, net profit to total assets, total liabilities to total assets, and current assets to current liabilities. Wallace's model had an overall prediction accuracy of 34% (Wallace, 2004).

Wanda tested a model using neural networks for predicting financial distress. This model used key financial ratios reported in previous studies as the best predictors, including working capital to total assets, cash flow to total assets, net profit to total assets, total liabilities to total assets, current ratio, and the quick ratio. Wanda's model, which tested 65 different financial ratios from past studies, achieved an impressive 94% prediction accuracy for financial distress (Wanda, 2004).

Benjamin and colleagues focused on predicting financial distress in high-tech industries listed on the New York Stock Exchange. They used 6 financial ratios, including 2 cash-related and 4 balance sheet and profit-loss ratios, employing logistic regression to study data from 60 bankrupt and 60 non-bankrupt companies from 2000 to 2002. Their composite model achieved 85% prediction accuracy for both bankrupt and non-bankrupt companies (Benjamin et al., 2005).

Khoshtaynat and Qasuri, in their study, estimated the case sample and analyzed nine financial ratios from cash flow and balance sheet items. Their results, based on the multiple discriminant analysis model, showed that a combination of financial ratios from the cash flow statement, balance sheet and profit-loss items were more effective than balance sheet and profit-loss ratios alone in predicting financial distress (Khoshtinat & Qasuri, 2005).

The first researchers to use both system dynamics and fuzzy logic together were Pankaj, Set, and Sushil in 1994. They developed a model for qualitative analysis of causal loops using fuzzy linguistic uncertainties to align the understanding of modelers. Most studies combining system dynamics and fuzzy logic aimed at describing fuzzy variables when data was unavailable (Kunsch & Springael, 2008).

Pirayesh and colleagues focused on liquidity ratios from the cash flow statement to predict financial distress. Their study used a sample of 40 bankrupt and 40 non-bankrupt companies from 2004 to 2006. The results showed that their model had prediction accuracies of 93.75% and 78.75% for one and two years before bankruptcy, respectively (Pirayesh et al., 2009).

Saidi and Aghai, in their paper titled "Predicting Financial Distress of Tehran Stock Exchange-listed Companies Using Bayesian Networks," proposed a prediction model using Bayesian networks. Their findings showed that discretizing categories from two to four improved the model's performance, but increasing the categories to five reduced the model's accuracy (Saidi & Aghai, 2009).

Mesaki, in his study, used logistic regression to examine 53 bankrupt and 53 non-bankrupt companies in Japan between 1973 and 1997. He tested 32 accounting variables (including 5 from the cash flow statement and 27 from the balance sheet and income statement), normalizing them by total assets, total liabilities, and total sales. The results showed that the normalized variables achieved prediction accuracies of 81.1%, 87.7%, and 78.3% for predicting financial distress based on total assets, total liabilities, and total sales, respectively (Mesaki, 2010).

Camposano et al. (2010) used system dynamics and fuzzy logic to strengthen supply chain management by simulating supply chain dynamics using fuzzy demand estimation.

Mousavi Shiri and Tabrizani used Data Envelopment Analysis (DEA) in their study and examined the role of efficiency in predicting financial distress in companies. They studied 60 companies listed in Tehran Stock Exchange from 2000 to 2010 and confirmed their results with the MDA technique. The findings revealed that efficiency plays a crucial role in predicting financial distress, as it can signal impending bankruptcy up to two years in advance (Mousavi Shiri & Tabrizani, 2012).

Mohseni and colleagues developed a model to predict financial distress in Tehran Stock Exchange-listed companies. They used efficiency alongside financial ratios as a predictor to improve prediction accuracy. Their findings indicated that efficiency significantly enhanced the model's prediction power (Mohseni et al., 2013).

Orji and Wei developed a modeling theory for supplier behavior in fuzzy environments using system dynamics, leading to more realistic supplier selection decisions (Orji & Wei, 2015).

Nasirzadeh and colleagues applied integrated system dynamics and fuzzy logic to evaluate the economic feasibility of BOT projects, using fuzzy numbers to estimate uncertain parameters and simulate project's Net Present Value (NPV) (Nasirzadeh et al., 2015).

Ahmadpour and Shahsavari investigated how managers' discretion in companies listed in Tehran Stock Exchange influenced the three stages of financial distress, using the Altman bankruptcy prediction model. Their study, based on panel data techniques, showed that managers manipulated accounting profits to portray a better financial position as companies approached bankruptcy (Ahmadpour & Shahsavari, 2014).

Other researchers, such as Sang and Zhang (2015) and Orji and Wei (2015), applied system dynamics models to simulate secondary scenarios and subsequently ranked them using multi-criteria decision-making techniques.

Desalles and colleagues explored the application of fuzzy logic in system dynamics to better model decision-making policies, particularly regarding uncertainty in model variables (Desalles et al., 2016).

Sterman and colleagues examined the use of System Dynamics modeling in the process of AI adoption in the financial services industry. The authors' model included various factors such as organizational readiness, costs, and feedback resulting from AI adoption (Sterman, et al., 2020).

Zhang and colleagues explored the complexities of Artificial Intelligence (AI) adoption in the financial sector using System Dynamics models, identified factors that affect the speed and success of this process (Zhang, et al., 2020).

Aini Zadeh and Gharib investigated the impact of financial ratios and ownership structure in predicting financial distress in companies. Using logistic regression to test hypotheses, their study covered 134 companies listed in Tehran Stock Exchange from 2014 to 2019. They found that the ratios of fixed asset turnover and total asset turnover negatively influenced financial distress, while inventory turnover and ownership structure had no effect (Aini Zadeh & Gharib, 2021).

Brown and colleagues used a System Dynamics approach to model the technology adoption process in the financial services industry, focusing specifically on AI. It simulates various interactions within the financial system (Brown, et al., 2021).

Noor and colleagues reviewd and analyzed various studies on the adoption of AI in financial institutions and explored different models, including System Dynamics models, used for analyzing AI adoption (Noor et al., 2021).

Shokhzadeh and Zafari explored the prediction of financial distress in Tehran Stock Exchange-listed companies using artificial neural networks, achieving prediction accuracy of 86%, 86%, and 90% for one, two, and three years before bankruptcy, respectively. Their study is distinct in analyzing financial distress from macroeconomic, financial, managerial, and risk perspectives and validating the use of both system dynamics and fuzzy logic algorithms (Shokohzadeh & Zafari, 2021).

Taghavib and colleagues used a System Dynamics approach to analyze AI adoption in banks, providing a case study of several large banks that have implemented AI (Taghavi, et al., 2024).

Nguyen and colleagues investigated the role of System Dynamics modeling in financial system innovations and its application in adopting new technologies such as AI (Nguyen, et al., 2022).

Zhang and colleagues evaluated the impact of AI on financial risk management using System Dynamics models (Zhang et al., 2023).

Farazi, in his study, analyzed the role of AI in managing emerging risks by comparing traditional approaches with machine learning (ML) and artificial neural networks (ANN). His study demonstrated that ANN and deep neural networks (DNN) outperformed traditional approaches by enhancing flexibility and performance under multiple risk factors (Farazi, 2024).

Mehrabi and colleagues proposed a hybrid model combining artificial immune systems (AIS) and neural networks (WNN) to predict financial problems. Their findings showed that the AIS-WNN hybrid model outperformed traditional methods in terms of prediction accuracy, sensitivity, and robustness (Mehrabi, 2024).

Wardhini et al. (2024) applied AI in a metamodel control system to manage crises, covering data collection, preprocessing, model monitoring, and optimizati.

Abdallavi and colleagues presented an innovative approach for predicting financial distress using weighted neutrosophic value distances, aiming to estimate the likelihood of financial distress for any company or organization (Abdallavi et al., 2025).

Methodology

System dynamics is a powerful methodology for gaining insights into issues with dynamic complexity and resistance to policymaking (Georgiadis & Bessou, 2008). It is a computer-based approach used to analyze and solve complex problems with a focus on policy analysis and design. Simulation using system dynamics models is highly useful for learning about the dynamic complexities of systems. It is also an essential tool for identifying optimal policies within existing systems, improving system behavior by changing parameters, and making structural changes. This approach has been applied across diverse fields, from production-distribution systems to ecosystems (Falo Lebsanev, 1999).

Steps of System Dynamics Modeling can be described as follows:

1. *Problem Definition*: This step involves clarifying the goal of the model. Clear articulation of the model's goal is essential for effective model development. Having a clear problem in mind facilitates the development of models that are practically suitable for the issue at hand.

2. *Variable Identification*: This involves identifying key variables that need to be included in the model to correctly represent the problem being examined. It is helpful to list all variables first, and then prioritize them.

3. *Reference Modes*: A reference mode is a pattern of behavior over time. Reference modes are depicted as charts of key variables over time. However, these charts do not necessarily represent observed behavior; they can reflect past or future behavior.

4. *Reality Checking*: This step defines certain scenarios for reality checking, concerning how variables are interrelated. Essentially, it involves understanding the reality and the relationships between factors. Changes in certain variables may have significant effects on other variables. Information on reality checking is often recorded as notes about the necessary relationships and is based on the knowledge the researcher has about the system under study.

5. *Dynamic Hypotheses*: A dynamic hypothesis is a theory about the structure that exists

and provides reference modes. A dynamic hypothesis can be presented in textual form, causal-loop diagrams, or flowcharts. Dynamic hypotheses can specify what is retained in the model and what is excluded. Like all hypotheses, dynamic hypotheses are not always correct, and revision is an essential part of developing a good model.

6. *Simulation Model*: A simulation model is a set of hypotheses expressed through a clear set of mathematical relationships. Simulation models generate behavior through simulation. A simulation model serves as an experimental environment where different structural elements that determine behavior can be tested and understood.

This process is iterative and flexible. As work progresses on a particular issue, an understanding of the problem may emerge that changes how the components are considered. Defining clear boundaries between the system under study and its external environment is a necessary step in the system dynamics approach (Georgiadis et al., 2005).

Studies conducted so far on financial distress have primarily focused on financial ratios, and none of them have considered the factors and variables affecting financial distress, which interact in a complex manner with each other. Moreover, the risks and uncertainties present in the systems have not been taken into account in most previous studies. This research aims to introduce an appropriate model for predicting financial distress in companies by using theoretical foundations and empirical evidence, integrating system dynamics simulation methods and fuzzy logic. This approach will address the aforementioned shortcomings and improve the accuracy of financial distress prediction.

In addition to key financial ratios for predicting financial distress, the goal is that the use of other variables as predictors can enhance the prediction accuracy and power of the model. Some of the factors to be examined in this study include external factors such as business fluctuations, competition, changes in economic structures, fraud, and economic volatility, and internal factors such as excessive credit sales, poor management, net profit, company performance score, debt quantity and quality, debt repayment capacity, production costs, interest expenses, and improper capital structure determination.

In this context, the system dynamics simulation method will be used to simulate the various parameters affecting financial distress and their interrelationships, as well as the specific project under consideration. Additionally, fuzzy logic will be used to account for the impact of qualitative factors on the project. To achieve this, all influencing factors on financial distress will first be identified, and a qualitative model of the project will be developed using causal feedback loops. Then, the mathematical relationships between the variables will be determined, and quantitative modeling will be carried out to assess the financial distress of the project. Finally, by using the developed quantitative model, the likelihood of financial distress, based on fuzzy input values, will be determined for the project, and the conditions of non-financial distress will be established by comparing different options under consideration.

Research Hypotheses

Based on the theoretical foundations presented and the objective of the research, the following hypotheses have been formulated:

1. First Hypothesis: What are the external factors influencing financial distress?
2. Second Hypothesis: What are the internal factors influencing financial distress?
3. Third Hypothesis: What is the model for the factors influencing financial distress?
4. Fourth Hypothesis: What are the scenarios for reducing financial distress?

Research Variables

1. Dependent Variable

Financial Distress

Financial distress refers to the inability of a company to meet its financial obligations. In this study, Article 141 of the Commercial Code is used as the criterion for identifying financial distress. Companies that fall under Article 141 of the Commercial Code are classified as financially distressed companies.

2. Independent Variables

To determine the independent variables, a review of the literature and previous research studies was conducted using library resources and interviews with specialists, experts, and professionals in the field of financial distress. Through the literature review and the Delphi method, the factors influencing financial distress were identified. After three stages of the Delphi technique, the following final criteria were selected.

Table 1.
Final Criteria for Financial Distress Based on Delphi Technique Results

No	Variable
1	Unemployment Rate
2	Debt Repayment Ability
3	Gross Domestic Product (GDP)
4	National Resources
5	Competition
6	Inflation
7	Export and Import Levels
8	Net Profit Level
9	Quantity and Quality of Debt
10	Excessive Credit Sales
11	Company Efficiency Score
12	Wage Increase Rate
13	Debt Service Coverage Ratio
14	Asset Coverage Ratio
15	Bank Debt to Debt Ratio
16	Production Costs
17	Payable Interest Costs
18	Inappropriate Capital Structure Determination
19	Ineffective Management
20	Fraud

(Source: Researcher's Findings)

Findings

In the system dynamics method, the first step is to understand the existing problem, and then, through discussions and consultations with experts, a causal-loop diagram is developed. After the causal-loop diagram is prepared, a flow diagram is created. At each stage of this process, revisions may be made to previous steps.

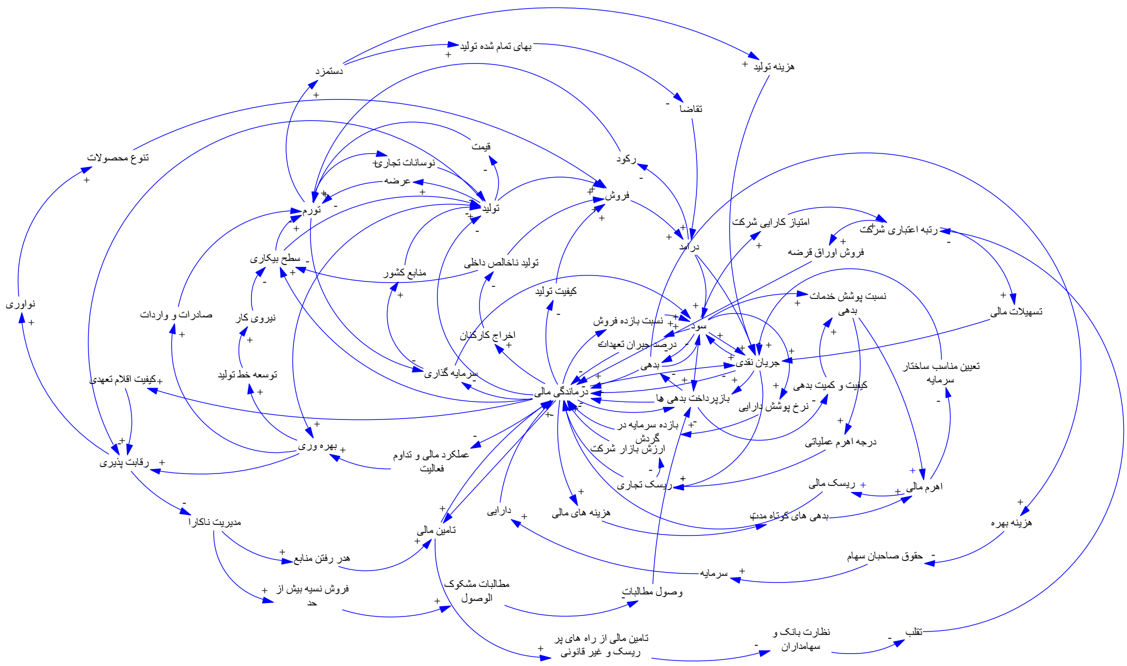
Using the causal-loop diagram, the relationships between variables are clearly illustrated. The causal-loop diagram for financial distress is shown in Figure 1. This model demonstrates that financial distress consists of various components, each of which is influenced by different factors. These influences may not be linear and could instead form a circular or feedback loop structure.

All the loops in this model are reinforcing, and some of the most important loops are described below.

For example, as the profit of an organization increases, its debts decrease, and with the reduction of debts, the organization faces less financial distress. With reduced financial distress, the organization can focus more on production and improve the quality of its products. As the quality of production improves, sales also increase, which in turn leads to higher revenue and profit for the organization.

Additionally, as the organization has more resources available, it can increase its production, which in turn leads to higher revenue. With increased revenue, the organization's profit also grows. As a result, the organization faces less financial distress and can make more investments, securing additional resources for the organization from the country.

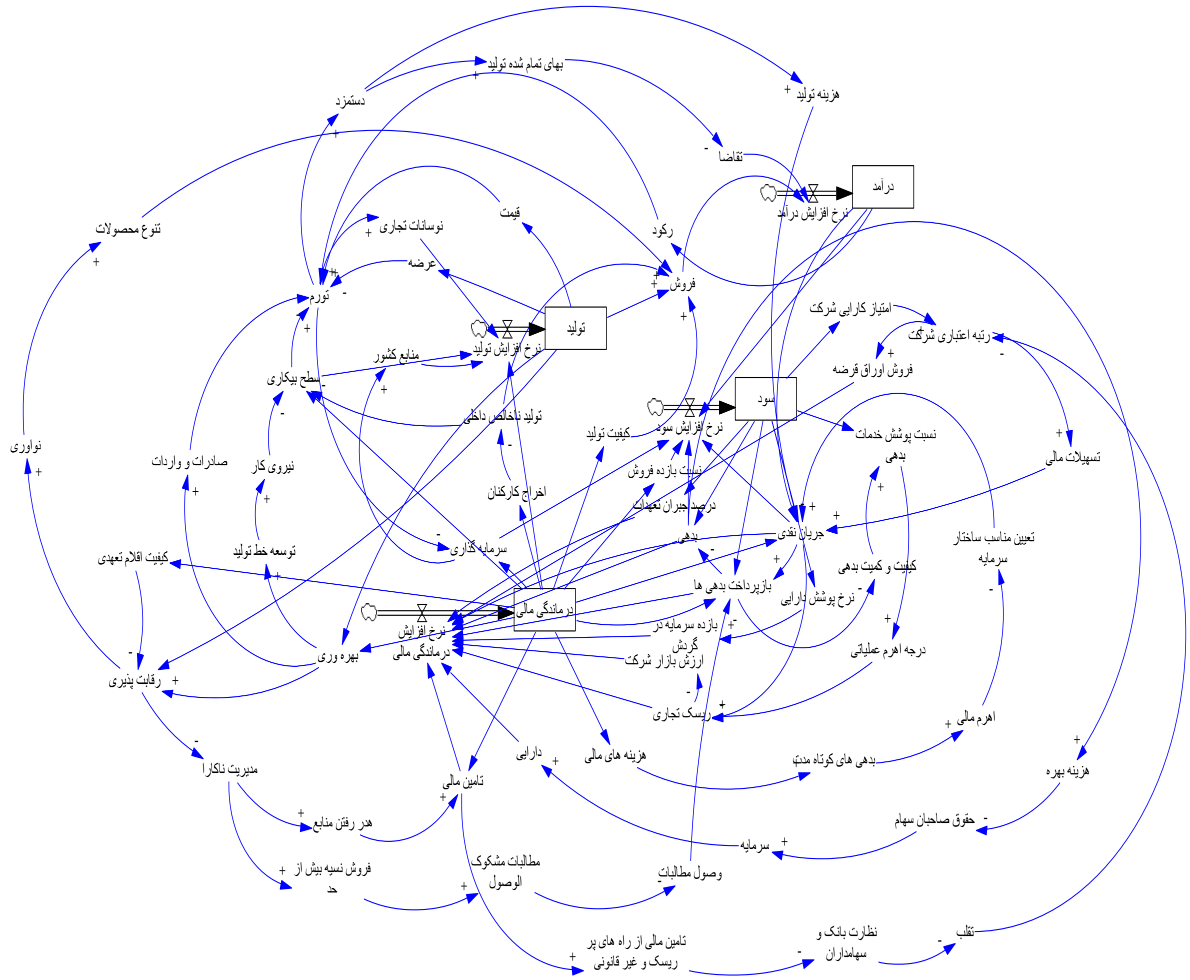
Figure 1.
Causal-Loop Model of Financial Distress



(Source: Researcher's Findings)

The state and flow diagram corresponding to the final causal-loop diagram is shown below. In this diagram, the variables of production, income, profit, and financial distress are considered as state variables, while other variables are treated as flow variables.

Figure 2.
State-Flow Diagram of the Model

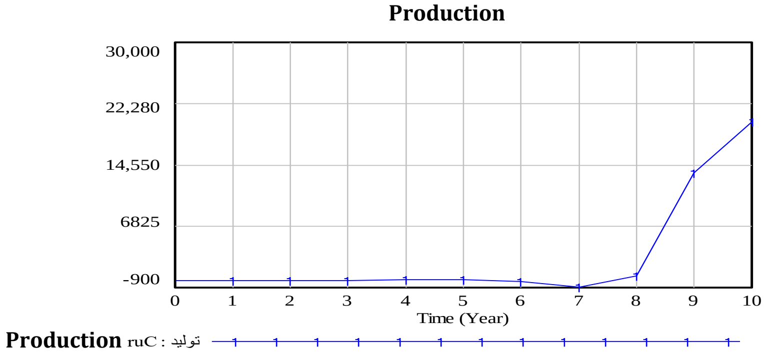


(Source: Researcher's Findings)

In the following, the initial behavior of some state and flow variables is shown in the figures below over a simulation period of 10 years. These results were obtained from simulating the state-flow diagram in Vensim software over a 10-year period.

1. The organization’s production over the ten-year simulation period shows an upward trend.

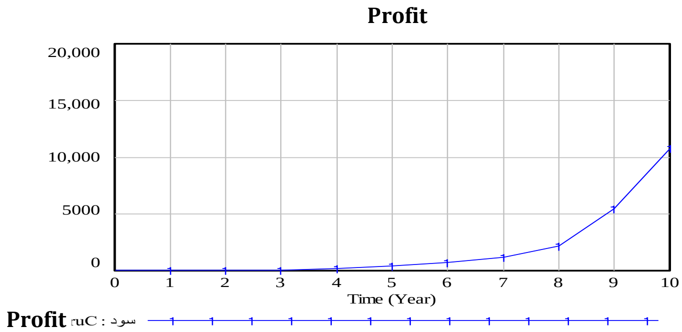
Figure 3.
Behavior of the Production Variable



(Source: Researcher's Findings)

2. The organization’s profit shows an upward trend over the ten-year simulation period.

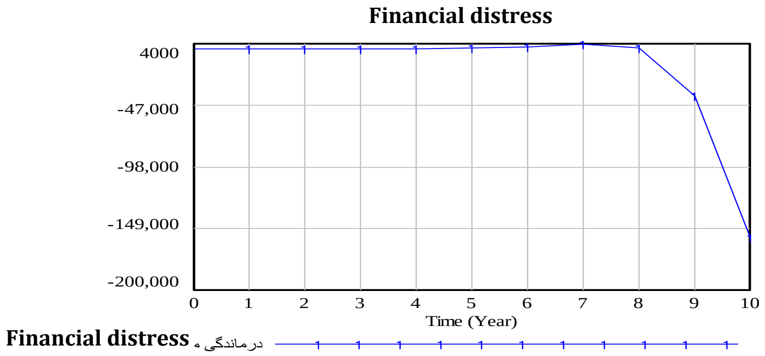
Figure 4.
Behavior of the Profit Variable



(Source: Researcher's Findings)

3. The financial distress of the organization shows a downward trend over the ten-year simulation period.

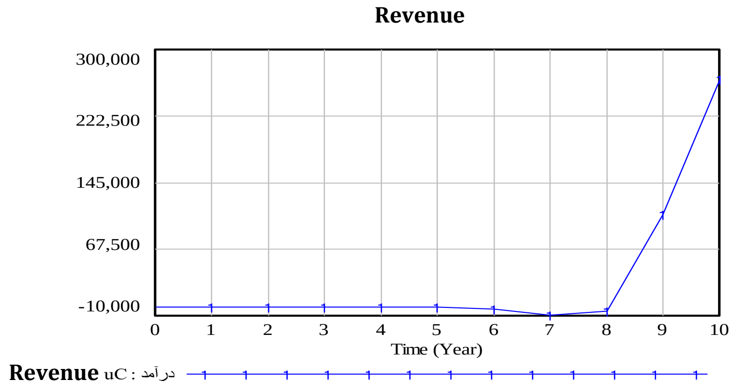
Figure 5.
Behavior of the Financial Distress Variable



(Source: Researcher's Findings)

4. The organization’s revenue follows an upward trend over the 10-year simulation period.

Figure 6.
Behavior of the Revenue Variable



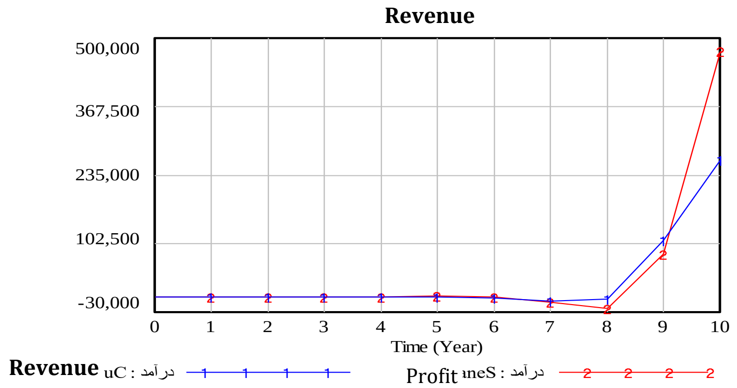
(Source: Researcher's Findings)

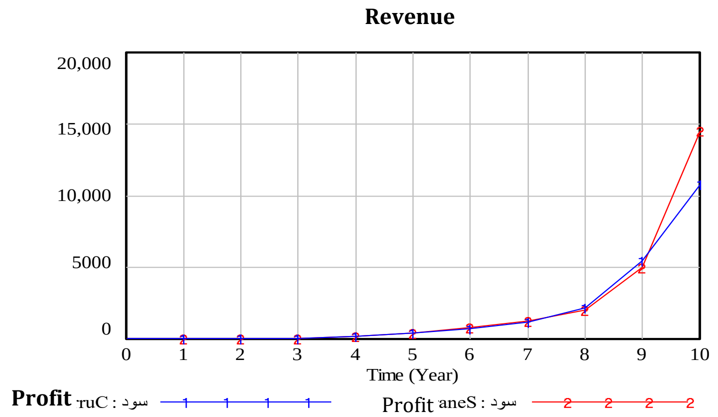
Then, scenarios related to the model were presented, which are outlined below:

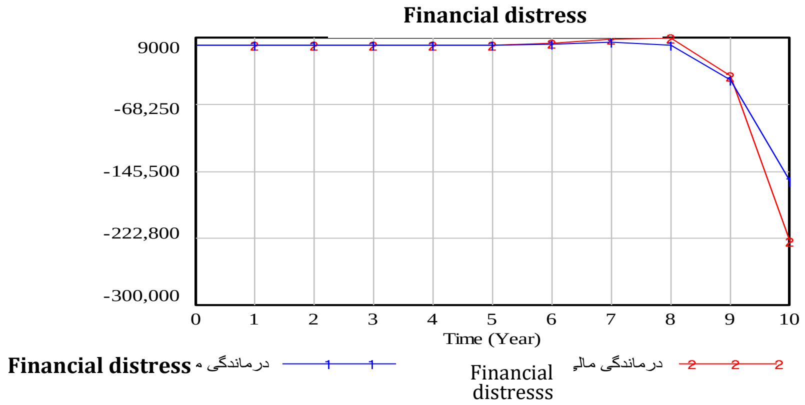
Scenario 1: Doubling Production

In this scenario, the increase in production is examined to evaluate the idea that by increasing production, revenue and profit can be raised, and financial distress can be reduced.

Figure 7.
Behavior of the variables income, profit, and financial distress with respect to the increase in production







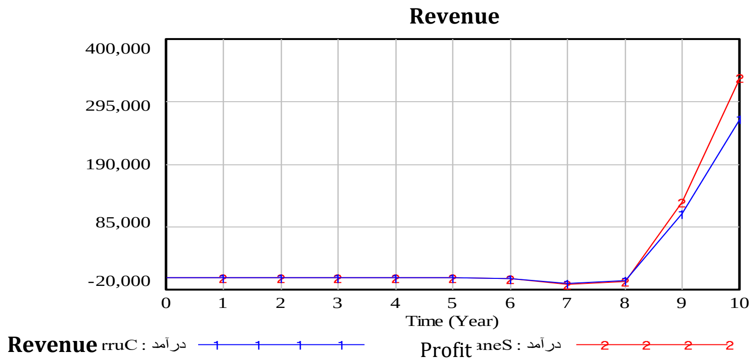
(Source: Researcher's Findings)

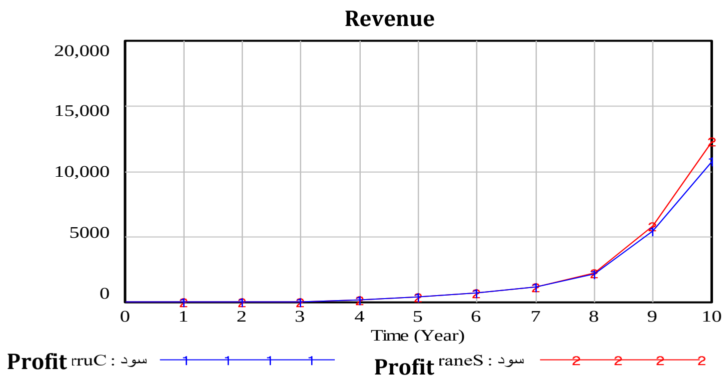
As seen in the above figures, this scenario produces our desired results, as ultimately, income and profit increase while financial distress decreases. Therefore, this scenario could lead to an improvement in the organization's situation in this case.

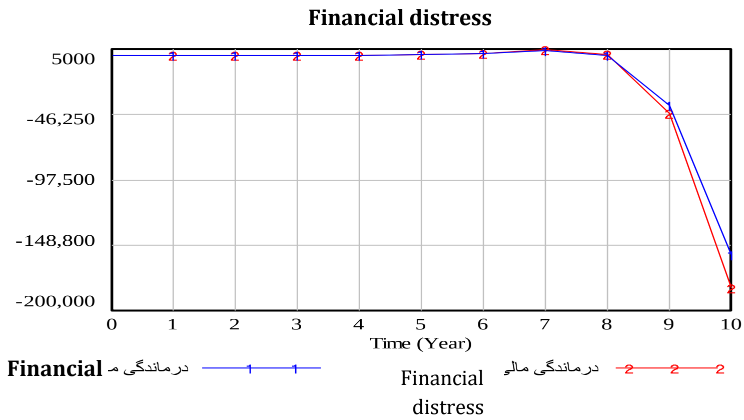
Scenario 2: Doubling the Demand

Next, the scenario of increasing demand is examined to improve the organization's situation through this scenario. The results of this scenario are presented below.

Figure 8.
Behavior of the variables income, profit, and financial distress with respect to the increase in demand







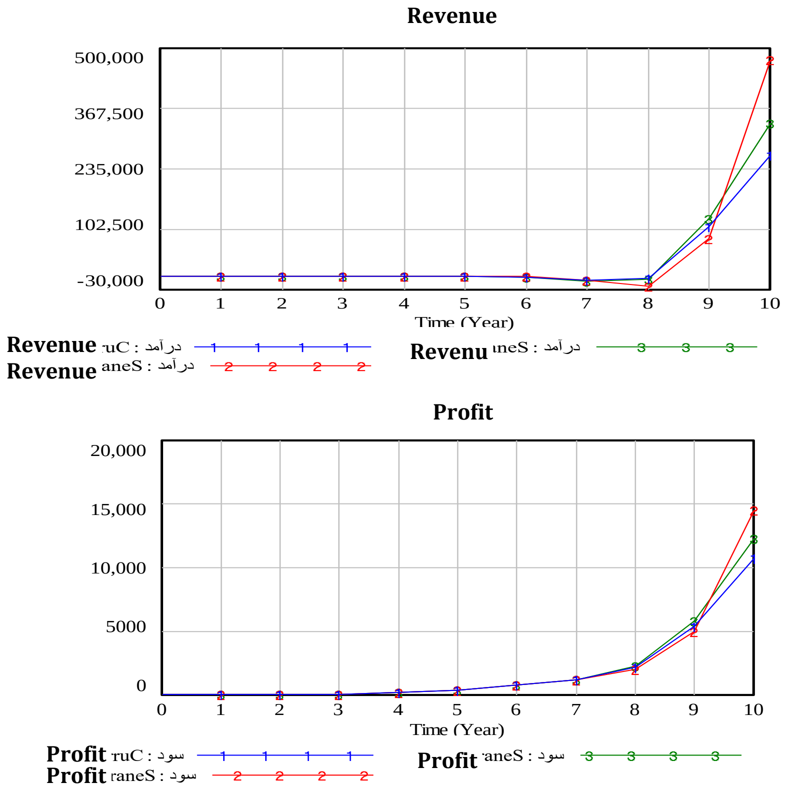
(Source: Researcher's Findings)

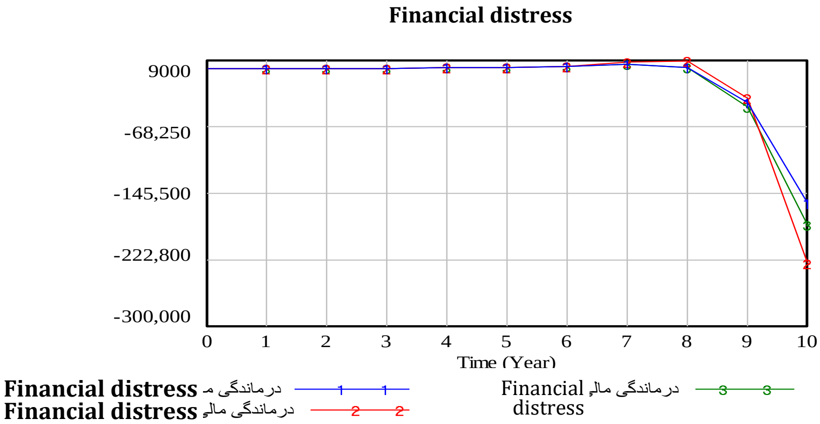
As shown in the above figures, this scenario also delivers the desired results, as it leads to an increase in income and profit, as well as a decrease in financial distress. Therefore, it can be considered as a solution for improving the organization's situation. However, to choose the best scenario, a comparison in terms of financial distress between them should be conducted, as detailed below.

Research Results

As shown in the figures below, Scenario 1 (doubling production) has resulted in the greatest reduction in the company's financial distress, as well as the highest increase in income and profit. Therefore, it can be selected as the best scenario.

Figure 9.
Result of the Best Scenario





(Source: Researcher's Findings)

Discussion and Conclusion

Given the development of companies, the increase in economic activities, intensifying competition, and the cycles of inflation and recession in recent decades, the number of financially distressed companies and the importance of financial distress have been rising. The issue of bankruptcy and financial distress has always been a significant concern. Financial distress and bankruptcy lead to the waste of resources and missed investment opportunities. Predicting financial distress by designing appropriate indicators and models can alert companies to the occurrence of financial distress and bankruptcy, allowing them to take appropriate measures in response.

Moreover, market participants, such as investors and financial institutions, need to be aware of the financial status and efficiency of existing companies. One method that can help in appropriately utilizing investment opportunities and better resource allocation is predicting financial distress or bankruptcy in companies. This way, companies can be alerted to financial distress, prompting them to take necessary actions, and investors and creditors can distinguish between favorable and unfavorable investment opportunities, channeling their resources into suitable investments. Thus, predicting financial distress and bankruptcy has always been a topic of interest to investors, creditors, and governments. Timely identification of companies facing financial distress is highly valuable, as it prevents investment in wrong or inefficient opportunities in the market.

Since this research uses a simulation model to provide solutions to prevent financial distress, it offers the advantage of changing various model variables in different combinations (which could encompass a large number of scenarios) without any cost. It allows for the observation of the behaviors resulting from policy changes and helps in selecting the best approach. It's important to note that evaluating policies in the real world through experience requires significant costs and time, leading to resource wastage. In contrast, simulation enables the evaluation of numerous policies with minimal time and cost.

It is also noteworthy that in previous research studies on financial distress, systems have mostly been studied in static environments or have only addressed the linear impact of a single factor on financial distress. However, the model presented in this study is a dynamic model that incorporates a large number of factors affecting financial distress and is time-dependent, showing the effects of changes over time. Additionally, since the model is a simulation of reality, it allows for observing, calculating, and analyzing the changes in various aspects of financial distress. In contrast, in previously proposed models, changes need to be made, and one must wait for the effects, which could potentially result in negative consequences if those changes are incorrect. Therefore, it can be stated that the model presented in this research has a particular advantage over previous models.

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Improving Tax Revenues in Iran's Provinces within the Framework of the Components of Knowledge-Based Economy

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ABSTRACT

A knowledge-based economy leads to a more efficient and dynamic national economy, contributing to the creation of more products, services, and innovation. Consequently, it brings about the outcomes of a stable economy, characterized by consistent and sustainable tax revenues. By focusing on innovation, advanced technologies, and specialized human capital, a knowledge-based economy plays a crucial role in improving the economic structure of the country. A knowledge-based economy is one in which the production, distribution, and application of knowledge are the main drivers of economic growth, wealth creation, wealth distribution, and job creation in all industrial sectors. The purpose of this research study is to investigate the impact of the knowledge-based economy on tax revenues in Iranian provinces. From the perspective of its purpose, this study is an applied study, and in terms of methodology, it is a panel data study, which has been conducted econometrically using the FMOLS panel data method. The findings indicated a positive and significant relationship between the components of the knowledge-based economy and tax revenues. As the components of the knowledge-based economy increase in Iranian provinces, tax revenues also rise. Furthermore, the model estimation, with the inclusion of auxiliary variables, showed that inflation rate, Gross Domestic Product (GDP), and government expenditures have a positive and significant impact on tax revenues, while the unemployment rate affects tax revenues negatively and significantly. Therefore, regional policymakers should prioritize enhancing human skills, expanding knowledge-based institutions, promoting innovative and creative centers, and developing technological infrastructure to increase tax revenues.

KEYWORDS

Information and Communication Technology, Innovation, Knowledge-Based Economy, Least Squares Method, Tax Revenues.

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Introduction

In today's world, national economies are undergoing profound and fundamental changes. The nature of production, trade, employment, and work will be vastly different in the coming decades. Previously, in the economy, natural resources were considered as the primary assets; however, in a knowledge-based economy, the production and utilization of knowledge play a major role in wealth creation, and the pace of change is extremely rapid. The new economy represents those aspects or sectors of an economy that are producing or employing new innovations and technologies to achieve long-term and sustainable growth (Sadeghi & Azarbaijani, 2006).

According to the definition provided by the Organisation for Economic Co-operation and Development (OECD), a knowledge-based economy is an economy that is shaped by the production, distribution, and application of knowledge and information. It is an economy in which investment in knowledge and knowledge-based industries receives special attention.

Many countries have concluded that a central strategy for achieving long-term and sustainable economic growth is to rely on the export of knowledge-based products and to embrace a knowledge-based economy. A knowledge-based economy is one where the creation and application of knowledge play a dominant role in wealth creation and drive economic growth and progress. Regarding tax revenue, it can be argued that taxation emerged simultaneously with the formation of the first human societies. A social economy, to fulfill its duties, resorts to tools referred to as institutions; one of these institutions is the government (Hadgoorpour, 2000).

Government revenue is broadly categorized into tax revenue and non-tax revenue. In many economies, tax revenue plays a far more significant role compared to other revenue sources, significantly mitigating the adverse economic effects compared to other revenue sources. Therefore, establishing a well-organized and systematic tax system creates a suitable environment for implementing various programs. These programs are usually planned within the framework of economic development plans, and economic goals must be predicted for their realization (Soltani & Porghafar Dastjerdi, 2013).

The tax system of each country plays a fundamental role in providing the financial resources for the government and the fair distribution of wealth. However, this system faces numerous obstacles and challenges that can reduce its efficiency. The most important obstacles are tax evasion, inefficiency in tax collection, complexity of tax laws, lack of transparency, and administrative corruption. The lack of effective government oversight leads to a decrease in tax revenues. Furthermore, inefficiency in tax collection, stemming from deficiencies in information systems and outdated technologies, can affect the overall performance of the tax system. The complexity of tax laws also causes confusion for taxpayers and increases compliance costs. In addition, administrative corruption and lack of transparency in the performance of tax officials reduce public trust in the tax system and lead to tax inefficiency (Khorshidi, 2024).

Therefore, examining the relationship between the knowledge-based economy and tax revenues is of particular importance. Research in this area can help officials and policymakers develop and implement programs that lead to greater utilization of knowledge and increased tax revenues.

This research identifies and analyzes specific components that can influence provincial tax revenues, such as innovation, education, technology, and scientific collaborations. Specifically, attention to these components can offer novel strategies for improving tax revenues that have not been addressed in previous research and can explore international experiences regarding the relationship between knowledge-based economies and tax revenues. By doing so, successful models can be examined and adapted to Iranian conditions, an often-overlooked issue in previous studies. Furthermore, it will contribute to a deeper understanding of the relationship between the knowledge-based economy and tax revenues in Iranian provinces, leading to the development of effective tax policies, particularly at the provincial level.

Since most economic studies related to the knowledge sector have examined only one or a few aspects, this paper aims to investigate the relationship between the components of the knowledge-based economy and tax revenues in Iranian provinces. In this regard, statistical data will be used to measure the knowledge-based economy and tax revenues. The research question is whether the components of the knowledge-based economy lead to increased tax revenues in Iranian provinces. This study tests the hypothesis that the knowledge-based economy and its components have a significant effect on tax revenues.

Literature Review

The Concept and Evolution of the Knowledge-Based Economy

The term "knowledge-based economy" was first coined by the Organization for Economic Co-operation and Development (OECD) and defined as economies based on the production, distribution, and use of knowledge and information. The knowledge-based economy emerged from a newly developing economic structure resulting from a major transformation and revolution based on knowledge and innovation. It has entered the economic sphere as a primary factor in generating welfare and serving as the engine of economic growth in knowledge-based societies, driving development. The United Kingdom was the first country to embrace this concept, followed by countries such as Canada, Australia, South Korea, China, Lithuania, Romania, Finland, Armenia, Scotland, New Zealand, Thailand, and others, which independently or with the assistance of international organizations, declared their readiness to adopt this economic model (Shaghaghi Shahri & Alizadeh, 2016).

A knowledge-based economy is the economic satationarygement of human capital, encompassing the education of all individuals in a society at the macro level and the training of the workforce in organizations and economic enterprises, at the micro level (Ghorbani, 2015). In a knowledge-based economy, knowledge is the primary driver and catalyst for wealth creation, economic growth, and employment across all sectors. Based on this definition, a knowledge-based economy is not solely dependent on a few industries relying on highly advanced technology; rather, all economic activities in this type of economy are, in some way, reliant on knowledge (Vahidi, 2002).

Dimensions of a Knowledge-Based Economy

To better understand a knowledge-based economy, it is necessary to identify broader knowledge dimensions that can meet the new knowledge needs of societies (Monavarian et al., 2007). Based on this, a knowledge-based economy is categorized into four main pillars, encompassing the development and effective application of knowledge. This section briefly examines the fundamental dimensions of a knowledge-based economy (Behboudi et al., 2015).

1. Trained and Specialized Workforce:

For the creation, acquisition, dissemination, and utilization of knowledge, a trained and specialized workforce is essential. Individuals with the necessary training can improve production factors and increase productivity, thereby promoting economic growth. Training can effectively identify the needs of organizations and the economy to perform their processes and adapt new technologies to domestic demands (Chen & Dahlman, 2004).

2. Innovation and Invention System:

Economic theories suggest that technological progress is a fundamental source of growth in productivity, and an efficient innovation system is key factor in technological development (Pilat & Lee, 2001).

A networked innovation framework refers to a set of institutions, regulations, and procedures that countries require to achieve the goals of acquiring, disseminating, and utilizing knowledge. Institutions within this innovation system include universities, public and private research centers, and policy-making bodies. These institutions engage in knowledge creation and development, its transfer, and policy measures through collaboration and interaction (Adams, 1990).

3. Appropriate Information and Communication Infrastructure:

The World Bank, as an international organization, defines information and communication technology (ICT) as a set of elements including hardware, software, networks, and media. These elements are used to categorize, store, process, transmit, and present information in text, audio, and visual formats via telephone, radio, television, and the Internet (World Bank, 2003). ICT, as the backbone of a knowledge-based economy, possesses many characteristics, including increased communication flow, reduced costs, decreased uncertainty in transactions due to rapid access to information, overcoming geographical limitations and increased competitiveness (Oliner & Sichel, 2000).

4. Institutional Regime and Economic Incentives:

The final pillar of a knowledge-based economy is the institutional structure and economic incentives operating on the basis of knowledge, innovation, and technology. In this economic system, price fluctuations are minimized, and global trade is free. Domestic industries must compete in this system without the need for protective regulations, and this competition stimulates entrepreneurship in the domestic economy. Government spending and budgets are controlled, and the financial system is capable of allocating resources to sound investments (Chen & Dalman, 2004).

Key indicators include education, human capital skills, information infrastructure, innovation systems, and the economic and institutional regime. Sub-indicators include adult literacy rates, telephone lines per 1000 people, patent filings, tariff and non-tariff barriers, postgraduate enrollment rates, computers per 1000 people, technological papers per million, regulatory quality, higher rates of education enrollment, Internet use per 1000 people, the number of science and technology researchers, and the role of regulations (World Bank, 2003).

Tax Revenues

In macroeconomics, taxation is recognized as a crucial tool for government economic policy. Since the formation of the first human societies, taxes have served as a source of income for rulers. The economic system of any society includes institutions such as households, firms, and the government. The government needs revenue to implement collective governance and provide public services, and its largest source of revenue is taxation (Ghadiri et al., 2014).

With the expansion of government responsibilities in recent times and the pursuit of goals such as economic growth, employment, and equitable income distribution, economic issues and challenges have significantly increased. These changes have led to increased complexity in economic satationarygement and created a need for new strategies and policies for the government (Soltani & Porghafar Dastjerdi, 2013).

Under various economic conditions, taxes can be used as an effective tool to guide the economy in the desired direction. During inflation, increasing income taxes can reduce the individuals' disposable income, thus decreasing household consumption, lowering prices, and easing inflationary pressure. Conversely, during a recession, reducing income taxes can increase consumption and demand, leading to higher prices (Rashti, 2001).

The Impact of the Components of Knowledge-based Economy on Tax Revenues

To increase the share of the tax revenues in income sources, it is necessary to reform the revenue system and design a tax system suitable for improving and upgrading the institutions of the knowledge-based economy, new technologies, and advanced infrastructure. As a result, the possibility of tax evasion will be reduced, and on the other hand, with the improvement of the inputs of the knowledge-based economy, the executive costs of the tax system will be reduced. Furthermore, with the realization of a knowledge-based economy, economic activities and consequently tax bases will increase, because with the improvement and upgrading of the components of the knowledge-based economy, we will face innovations and an increase in knowledge-based products and services. As a result, the government tax revenues will increase (Shahabadi et al., 2022).

In the last two decades of the 20th century, economic theorists such as Roemer, McLuhan, and Drucker predicted the emergence of a new economic era. In this era, knowledge is recognized as the primary source of wealth and is considered as the main factor in economic production. In the so-called knowledge age, the importance of knowledge in wealth creation and economy is very high. Knowledge, as a superior resource, plays a significant role in achieving the economic growth and progress (Azimi & Barkhordari, 2008).

The Impact of Inflation Rate, Government Expenditure, Gross Domestic Product, and Unemployment Rate on Tax Revenues

Inflation is one of the factors affecting taxes. As inflation increases, due to rising inflationary expectations, price transmission becomes easier, and the acceptance of taxes, as it leads to increased final consumer prices, results in increased tax revenues. With increased inflation in the economy, the prices of traded goods and services increase, and through this, the value-added tax received from the exchange of goods and services increases. Consequently, tax revenues also increase. To examine the effect of inflation on tax revenues, the effect of inflation on the final profit in economic activities must be considered to ultimately judge the effect of inflation on taxes. Therefore, the ultimate impact of inflation on the amount of tax revenue depends on the overall elasticity of tax revenue to inflation (Totonchi Maleki et al., 2020).

Based on the causal relationship between expenditure and taxes, the revenue response relative to the previous year is established. The government first spends and then decides how to finance these expenditures, if necessary, through increased taxes. This relationship suggests that the government budgets and forecasts its future tax liabilities based on the current government's borrowing. Therefore, an increase in government expenditure leads to an increase in taxes (Rezaei & Shahidi, 2015).

In national accounts, Gross Domestic Product (GDP) can be considered as a flow of income or output. This relationship shows the connection between tax revenue and Gross National Product (GNP). The composition of national production, including the agricultural, service, and industrial sectors' shares of the economy, can influence the level of tax revenue. Industry is recognized as the engine of economic growth and capital accumulation. With its dual characteristics of job creation and income generation throughout the economic cycle during the development process, the industrial sector leads to increasing per capita income. As the value added by the industrial sector increases, followed by increases in employment and per capita income, tax evasion decreases, and tax collection increases. Furthermore, the impact of taxation on agricultural sector is indirect; it occurs through the payment of taxes on consumed goods and services, leading to increased government tax revenue (Totonchi Maleki et al., 2020).

Generally, unemployment can negatively impact government tax revenues because individuals have lower incomes and therefore do not pay as much wage tax. Increased unemployment leads to a decrease in consumer spending, as unemployed individuals consume less, which can further reduce tax revenues. The tax system in the Iranian economy is not designed based on the full production capacity. Therefore, even with a decrease in economic capacity, tax revenue may increase. This is due to the identification of new tax bases. Secondly, unemployment statistics in the Iranian economy are not accurate, and individuals employed in the service sector may be considered unemployed while having high incomes. Therefore, these inaccuracies in unemployment estimates are a major reason for the lack of a significant impact of unemployment on taxation (Alizadeh et al., 2023).

Research Background

Domestic Background

In a reseach study, Siahpoush (2023) concluded that human capital, through innovation, contributes to increased productivity, social participation and cohesion, entrepreneurship, and a belief in science and scientific insight, continuous and lifelong learning, and impacts good governance, leading to the realization of a knowledge-based economy in the country. Safardoost and colleagues (2022) conducted a research study and presented a model to examine the role of intellectual and social capital in the components of a knowledge-based economy in Iran. Their findings indicated that social and intellectual capital play a significant role in the knowledge-based economy, and that social capital can play a more effective role through the improvement and enhancement of intellectual capital. Ali-Nezhad and colleagues (2021) conducted a study and classified Iranian provinces based on regional knowledge-based economy indicators using the c-means and fuzzy k-means clustering algorithms. The findings showed a significant heterogeneity among the provinces in terms of knowledge-based economy; Tehran and Alborz were in a separate cluster and considered leading provinces, while more than half of the provinces were in the lowest cluster of the classification. Rahimi (2019) conducted a research study on measuring and prioritizing regional competitiveness in Iran based on the components of knowledge-based economy, finding that production, inventions, and the number of knowledge-based companies have a positive impact on regional competitiveness. An increase in ideas translated into production, inventions, knowledge-based companies, etc., leads to increased competitiveness. Ghaffary fard & Maleki Nasr (2021) investigated the impact of knowledge-based economy on the economic growth of Iranian provinces, demonstrating a significant, positive, and long-term impact of the composite knowledge-based economy index on economic growth. Raghfar (2018) researched the impact of knowledge economy components on entrepreneurship in selected countries. The results showed that in resource-based countries, the components of knowledge-based economy, except for information and communication technology, had a significant positive impact on entrepreneurship during the study period. In innovation-driven countries, all the components of knowledge-based economy had a significant positive effect on entrepreneurship. In another study, Kahraei (2018) examined the impact of knowledge-based economy companies and innovative startups in science and technology parks on regional economic growth in Iran. The results indicated a significant positive impact of the number of knowledge-based companies and their sales on regional economic growth. Khodaverdi Zadeh et al. (2017) conducted a research study on the role of the knowledge-based economy in achieving the goals of the Resistance Economy, focusing on national production and employment as envisioned by the Supreme Leader. Their findings indicated that the indicators of knowledge-based economy have a positive impact on the country's Gross Domestic Product (GDP), a symbol of the Resistance Economy. Asnafi et al. (2015) investigated the role of university libraries in developing the knowledge-based economy within the branches of Islamic Azad University in Tehran. Their results showed that the components of knowledge creation, dissemination, and application were poorly implemented in these libraries. Therefore, university libraries play a minimal role in developing a knowledge-based economy. Mohaqeqi Kamal et al. (2013) estimated a composite social welfare index for Iran, evaluating economic welfare using several indicators. Their findings showed a decreasing trend in the index until the mid-point of the study period, followed by an increase. Based on this index, social welfare had both its best and worst performance during the study period. Dizaji et al. (2012) studied Iran's position in the knowledge-based economy among selected countries. Using Data Envelopment Analysis (DEA), they evaluated Iran's position against 40 other selected countries. Their results placed the United States first, China second, and Switzerland third. These countries, along with Norway, Singapore, Finland, and the United Kingdom, exhibited equal efficiency. Iran ranked as 29th with an efficiency score of 0.0946. Nazeman and Eslami-Far (2010) explored the relationship between knowledge-based economy and sustainable development. Their findings indicated a significant global correlation between economic development and the knowledge intensity of the economy. Another finding confirmed the overall validity of the Environmental Kuznets Curve (EKC) on a global scale.

Foreign Background

Saba and Monkam (2025), in a study on the role of Artificial Intelligence (AI) in enhancing tax revenue, institutional quality, and economic growth in selected BRICS-plus countries, concluded that there is a bidirectional causal relationship between tax revenue and AI, economic growth and institutional quality, as well as institutional quality and tax revenue. They emphasized that integrating AI into tax systems can promote both short- and long-term economic growth. However, they advised caution regarding the interaction between AI and institutional quality, which does not support economic growth, and highlighted the need for taking strong measures to mitigate potential negative effects of this interaction. Judijanto (2024), found that although there are initially promising signs, there is insufficient statistical evidence to confirm a significant effect of tax increase strategies on the tax revenue ratio within the studied sample. Similarly, the digital economy does not appear to have a significant impact on the tax revenue ratio. Furthermore, no significant moderating effect of the digital economy on the relationship between tax increase strategies and the tax revenue ratio was observed. Senawi et al. (2024) concluded that the process innovation mediates the relationship between both structural and relational performance of capital and property tax reassessment. This suggests that local government policies indirectly influence reassessment through implementing new administrative and technological methods. Additionally, positive stakeholder relationships encourage staff to develop innovative ideas, enhancing reassessment outcomes. Ciucci (2024), in a study on the impact of education on tax evasion and the shadow economy, concluded that increasing the general level of higher education can reduce tax evasion and the size of the shadow economy, emphasizing a significant negative correlation between education and shadow economy. Elsayed (2023) found multiple benefits of using ontology in tax management, including cost reduction in tax advisory services, minimizing errors in tax calculations, and increasing tax revenues through enhanced transparency and accountability. The empirical analysis also confirmed a positive correlation between ontology-based knowledge management and improved accountability practices, as well as reduced tax risks.

Aparicio et al. (2023) identified seven thematic clusters of foundations of knowledge economics, knowledge economics satationarygement, knowledge-based work, knowledge production, knowledge-intensive environments, knowledge-based capitalism, and the reconceptualization of knowledge-driven economics, providing a general overview of this field. Ben Hassan (2024), in a study of Lebanon's competitive knowledge-based economy, concluded that the transition to a knowledge-based economy in Lebanon is influenced by two opposing factors: the education system and entrepreneurial culture on the one hand, and political instability on the other. In fact, the move towards a knowledge-based economy in Lebanon is supported by its highly skilled and multilingual human resources, a result of a reliable education system strengthened by a strong entrepreneurial spirit. However, several issues such as weak infrastructure, inefficient ICT and public institutions, and brain drain hinder the transition to a knowledge-based economy. Uyar et al. (2024) conducted an empirical analysis on a sample of 142 countries for the period 2006-2015 and found that the quality of general, mathematics, and satationarygement science education significantly reduces the tax evasion. Rim et al. (2019) examined the key indicators for determining the status of a knowledge-based economy and the statistical methods for its evaluation in their research. Polyakov et al. (2018) used the components of education, production technologies, science, information and communication technologies, and innovative businesses to assess the level of a knowledge-based economy during 2010-2014, aiming to cluster the selected countries using the k-means algorithm. Bakirci (2018) employed the components of a knowledge-based economy introduced by the World Bank and the innovation index to examine the status of the knowledge-based economy in Turkey. By introducing a new index, Delgado Marquez and Garcia Velasco (2017) clustered different European regions based on the weighted average of various knowledge-based economy indicators and the k-means algorithm. This composite index measures the access to specialized knowledge resources in a region, typically embedded in regional actors across Europe. Hsu et al. (2008) investigated the competitive policies for technological innovation in the knowledge-based economy era. The findings indicated a positive impact of competitive policies on technological innovations. Tan and Hooy (2007), in their paper on the development of Southeast Asian countries towards a knowledge-based economy, used Data Envelopment Analysis to examine the performance of selected countries using both graphical and Data Envelopment Analysis methods. They assessed the knowledge gap and performance of the selected countries in their movement towards a knowledge-based economy.

Overall, while these studies offer substantial insights into the mechanisms underpinning KBE development and fiscal behavior, the ongoing challenges, such as political instability, inadequate infrastructure, and the need for tailored educational policies, demand further investigation and localized strategies to effectively leverage the potential of knowledge economies across diverse contexts.

This study, adopting a novel approach, examines the impact of the knowledge-based economy on tax revenues of Iranian provinces, presenting significant differences compared to the previous research. Through the use of a distinct methodology and multidimensional analysis, this research comprehensively investigates the effects of the knowledge-based economy at various provincial levels, facilitating the generalization of results to diverse geographical and economic locations. Furthermore, this study emphasizes specific components of the knowledge-based economy, such as innovation, information technology, and education. The practical findings of this study can assist policymakers in reforming and improving tax policies. Overall, by providing deeper and more practical analyses than the existing literature, this research offers added value to the field of the knowledge-based economy and its connection to tax revenues.

Methodology

This research is applied in terms of its objective and uses panel data in terms of its methodology. Panel data combines time-series and cross-sectional data, analyzing observations across several cross-sectional variables over a specific time period. This study identifies the impact of the components of knowledge-based economy on tax revenues in Iran’s provinces using a composite index to achieve the desired results. The information, statistics, and data used in this research study, covering the years 2011-2019, were collected from the Statistical Center of Iran, statistical yearbooks, and the website of Ministry of Economy and Finance. The analysis employed the FMOLS (Fully Modified Ordinary Least Squares) panel econometric method, using the necessary tests in Eviews version 12.

The independent variables are the composite components of the knowledge-based economy, namely: the innovation system, information and communication technology (ICT), education, economic incentives, and the institutional regime. The dependent variable in this study is tax revenue in Iranian provinces. The control variables include Gross Domestic Product (GDP), government expenditure, unemployment rate, and inflation rate. These were incorporated into two models. The first model estimates the effect of the four components of the knowledge-based economy on tax revenue, while the second model estimates the effect of the composite components of the knowledge-based economy (obtained using the Morris method) and the aforementioned control variables on tax revenue.

$$Yij = \left(\frac{Xij - XI\ min}{Ximax - Xi\ min}\right)*100$$

In the first model, Iranian provincial tax revenues are influenced by the components of a knowledge-based economy including skilled and specialized workforce, innovation and invention systems, information and communication infrastructure, and the components of the economic incentives and institutional regime.

$$Tax\ Revenue = \alpha + \beta1Education + \beta2Innovation + \beta3Economic\ incentives + \beta4ICT + U$$

In the second model, Iranian provincial tax revenues are affected by inflation rate, Gross Domestic Product, government expenditure, unemployment rate, and a composite component of the knowledge-based economy.

$$Tax\ Revenue = \alpha + \beta1lGDP + \beta2lGCE + \beta3INF - \beta4NEM + \beta5lMOALIFA + U$$

Findings

This study has been examined using two models.

The First Model

In the first model, we examined the impact of the components of knowledge-based economy on tax revenues. Before model estimation, we conducted the Stationarity tests, followed by Hausman and Chow/Fisher tests.

The Stationarity Test

Given concerns about the stochastic processes and spurious regression of variables before estimation, the presence of unit roots in the variables is investigated. Therefore, before model estimation, to ensure that the results are not spurious and reliable, it is necessary to ensure the stationarity of the variables.

The stationarity test is primarily conducted to prevent spurious regressions. To avoid the spurious regression, the variables must be stationary. Otherwise, the differences of the variables, which are usually stationary, should be used.

Table 1.
The Stationarity Test of the First Model

Variable	Statistic	Prob	dynamic
Tax	8/66869	0.0000	Stationarity(2) I(1)
ICT	-6/94244	0.0000	Stationarity I(1)
Education	-30/5211	0.0000	Stationarity I(1)
Innovation	-5/66306	0.0000	Stationarity I(1)
E.incentives	-39/7658	0.0000	Stationarity I(1)

(Source: Researcher's Findings)

Chow's Test (F-Limer)

This test distinguishes between pooled OLS estimation and fixed effects estimation. If the null hypothesis (H0) is confirmed in this test, it means the model should be estimated using pooled OLS regression; rejection of the null hypothesis indicates that a panel data approach is appropriate.

Table 2.
Chow's Test of the First Model

Effects Test	Statistic	D.f	Prob
Cross-section F	12/642780	30/180	0.0000
Cross-section Chi-Square	244/389585	30	0.0000

(Source: Researcher's Findings)

Given the table above, the test statistic is less than 5 percent. This indicates that the null hypothesis (H_0) is rejected, and the model estimation was performed using the fixed effects regression.

Hausman Test

The Hausman test can be used to distinguish between fixed-effects and random-effects models in panel data. Under the null hypothesis, the random-effects model is preferred due to the higher efficiency of its estimator. However, if the null hypothesis is rejected, the fixed-effects model is preferred.

Table 3.
Hausman Test of the First Model

Test Summary	Chi-S q. Statistic	C h-S q .d .f.	Prob
Cross-section random	58/869230	4	0.0000

(Source: Researcher's Findings)

Hausman test results indicated that the calculated statistic is smaller than the table statistic. Therefore, the null hypothesis (H_0) is rejected, and the model will be estimated using the fixed effects regression.

To estimate the relationship between tax revenues (dependent variable) and composite indicators of the knowledge-based economy (explanatory variables), the following model is presented. The results of this estimation for 31 provinces of the country during the years 2013-2019, using EViews software and the fully modified ordinary least squares (FMOLS) method, are presented in Table 4.

Table 4.
Summary of the First Model

Variables	Coefficient	Std. Error	t-Statistic	Prob
Inovation	0/033883	9/55E-15	3/55 E+12	0.0000
E.incentives	-0/005802	4/05E-15	-1/43E+12	0.0000
ICT	0/098611	3084 E-15	2/57 E+13	0.0000
Education	0/024426	9/34 E-15	2/20 E+14	0.0000
R2	0/99			

(Source: Researcher's Findings)

Based on the research results in Table 4, a one-unit increase in innovation leads to a 0.03-unit increase in tax revenues, as their relationship is positive and significant.

Incentives, however, have a negative and significant relationship with tax revenues; a one-unit increase in this variable results in a 0.00-unit decrease in tax revenues. The next variable, technology, has a positive and significant relationship with tax revenues, with a one-unit increase leading to a 0.09-unit increase in taxes. Finally, education also shows a positive and significant relationship with tax revenues; a one-unit increase in education and skilled labor results in a 0.02-unit increase in tax revenues.

The R-squared value in this model is 0.99, indicating that 99% of the variation in tax revenues across the country's provinces is explained by the variables in the model. This means the model has a high explanatory power.

The Second Model

In this model, in addition to the four components of a knowledge-based economy, other auxiliary indicators have been included, namely Gross Domestic Product, government expenditure, inflation rate, and unemployment rate. The impact of these variables on the dependent variable, tax revenue, was examined. As in the first model, stationarity tests, Chow test, and Hausman test were performed, which are discussed below.

Stationarity Test of the Second Model

Table 5.
Stationarity Test of the Second Model

Variable	Statistic	Prob	dynamic
Tax	-9/32788	0/0000	Stationarity I(1)
GDP	-18/7075	0/0000	Stationarity(2) I(1)
GCE	-36/1318	0/0000	Stationarity I(1)
INF	-9/88362	0/0000	Stationarity(2) I(1)
NEM	-13/0729	0/0000	Stationarity I(1)
MOALIFA	-32/9657	0/0000	Stationarity I(1)

(Source: Researcher's Findings)

Chow's Test of the Second Model

Table 6.
Chow's Test of the Second Model

Effects Test	Statistic	D.f	Prob
Cross-section F	6.261251	30/181	0.0000
Cross-section Chi-Square	154.473445	30	0.0000

(Source: Researcher's Findings)

Given a Chow test probability (prob) of less than 0.05, the null hypothesis (H0) is rejected, and a fixed-effects regression or panel data method is used.

Hausman Test of the Second Model

Table 7.
Hausman Test of the Second Model

Test Summary	Chi-S q. Statistic	C h-S q .d .f.	Prob
Cross-section random	14/731273	5	**0.0116**

(Source: Researcher's Findings)

The Hausman test results in Table 7 show that the calculated statistic is smaller than the critical value. This indicates that the null hypothesis (H_0) is rejected, and the model is estimated using the fixed effects regression.

Table 8.
Summary of the Second Model

Variable	Coefficient	Std.Error	t-Statistic	Prob
LGDP	0.576237	0.82176	7.012203	0.0000
LGCE	0.420994	0.029617	14.21447	0.0000
INF	0.014841	0.004519	3.283952	0.0012
NEM	-0.010627	0.004745	-2.239905	0.0264
LC.K B E	0.816013	0.134434	6.070002	0.0000
R2	0.67			

(Source: Researcher's Findings)

As shown in Table 8, a one percent change GDP leads to a 0.57 percent change in tax revenues; a one percent change in government spending leads to a 0.42 percent change in tax revenues; and a one percent change in inflation leads to a 0.014 percent change in tax revenues. The relationship between these variables and tax revenues is positive and significant.

Furthermore, a negative relationship exists between tax revenues and the unemployment rate. A one percent increase in the unemployment rate results in a 0.01 percent decrease in tax revenues. The combined components of the knowledge-based economy also have a positive relationship with tax revenues, such that a one percent change in this variable causes a 0.81 percent change in tax revenues.

The R-squared value in the above model is 0.67, indicating that the model has acceptable explanatory power.

Discussion and Conclusion

This study made an attempt to explain the effect of the combined indicators of a knowledge-based economy on tax revenues. Using the statistical data of twelve components of the knowledge-based economy, combined using the Morris method, and data of explanatory variables used in the model specified in this research during the years 2013-2019, a panel data approach with the Fully Modified Ordinary Least Squares (FMOLS) method was employed.

Based on the research results, a one-unit increase in innovation led to a 0.03-unit increase in tax revenues, as their relationship was positive and significant. Incentives, however, had a negative and significant relationship with tax revenues; a one-unit increase in this variable resulted in a 0.005-unit decrease in tax revenues. The next variable, technology, had a positive and significant relationship with tax revenues, with a one-unit increase leading to a 0.09-unit increase in taxes. Finally, education also showed a positive and significant relationship with tax revenues; a one-unit increase in education and skilled labor resulted in a 0.02-unit increase in tax revenues.

The R-squared value in this model was 0.99, indicating that 99% of the variation in tax revenues across the country's provinces was explained by the variables in the model. This means the model has a high explanatory power.

By incorporating auxiliary variables such as the unemployment rate, inflation rate, GDP, and government expenditure, a positive and significant relationship between tax revenues and inflation rate, GDP, and government expenditure was established. A negative and significant relationship between tax revenues and the unemployment rate was also evident.

This aligns with Uyar et al. (2024), who also found that the quality of education correlated negatively with tax evasion, supporting the idea that improved education can enhance fiscal compliance. Moreover, the positive relationship between inflation, GDP, and government expenditure with tax revenues echoes Marcel et al., who highlighted the macroeconomic impacts of these factors in Indonesia, as well as Iriqat and Anabtawi (2016), who reported similar findings for Palestine. In contrast, the negative correlation between incentives and tax revenues in this research suggests that poorly designed tax incentives may lead to reduced revenues, a perspective that warrants further investigation. Furthermore, while the literature, including Ben Hassan (2023), emphasizes the dual influences of education and political stability in transitioning to a knowledge-based economy, this research contributes to the quantitative assessment of how specific knowledge economy components impact tax revenues, thereby enriching the body of knowledge and offering a nuanced understanding of how various factors converge to shape tax policy and economic outcomes. Overall, this study underscores the importance of investing in education and innovation while reconsidering tax incentive structures to optimize tax revenue generation within a knowledge-based economic framework.

Based on the vital role of the knowledge-based economy in advancing political and economic goals, governments have prioritized creating job opportunities and increasing tax revenues through the expansion of research institutes, research and technology centers, and the encouragement and support of innovation systems. They have designed the necessary mechanisms and frameworks to develop the infrastructure related to the pillars and components of the knowledge-based economy and created the necessary incentives. According to the research model's output, the following suggestions, considering the research topic, can be used to improve the knowledge-based economy by enhancing its four dimensions of economic and institutional regime, education, innovation, and information and communication technology (ICT).

1. Strengthening Education and Human Resources

To cultivate a skilled workforce essential for contributing to the knowledge-based economy, it is critical to enhance the quality of scientific education. This can be achieved by revising curricula to emphasize critical thinking, problem-solving, and creativity, thereby preparing students to meet the market demands effectively. Additionally, promoting lifelong learning initiatives through continuous education and vocational training programs that align with industry needs will enhance workforce adaptability and productivity. Expanding STEM education and career pathways by increasing scholarships and mentorship opportunities in science, technology, engineering, and mathematics (STEM) disciplines will further build a pipeline of skilled talents.

2. Reforming the Innovation System

To develop a robust innovation ecosystem, policymakers should implement structural reforms to support Research and Development (R&D). This includes providing tangible incentives, such as grants and tax relief, for both public and private sector investments in R&D. It is also essential to revise the laws of intellectual property rights to strengthen the intellectual property framework, encouraging innovation and protecting the interests of inventors to enhance competitiveness. Furthermore, fostering public-private partnerships will create collaborative programs between universities and industry, facilitating the knowledge transfer and commercialization of research.

3. Enhancing Information and Communication Technology (ICT) Infrastructure

A comprehensive ICT infrastructure is vital for knowledge dissemination and economic growth. Recommendations include developing comprehensive e-governance systems that implement electronic tax registration and payment systems to streamline tax compliance, thereby improving efficiency, transparency, and taxpayer utilization. Investing in broadband connectivity, particularly in underserved rural areas, will ensure that all citizens and businesses can participate in the digital economy and benefit from industry innovation. Encouraging technology transfer from academic institutions by promoting universities as hubs for technology transfer and entrepreneurship, disseminating research outcomes through dedicated technology transfer offices and innovation incubators, is also critical.

4. Improving Economic and Institutional Frameworks

Creating a conducive environment for tax revenue growth requires focused efforts to establish a stable legal and regulatory environment. Clear, consistent, and enforceable regulations are necessary to safeguard businesses and promote fair competition. To combat corruption and build trust, robust measures should be implemented to reduce corruption and enhance governance, thus boosting investor confidence and ensuring an equitable economic environment. Policymakers should exercise prudence in the formulation of tax policies, carefully considering the potential effects of tax base expansion on economic activity. This includes conducting regular assessments of the tax system to identify inefficiencies and potential areas for growth that do not negatively impact the economy. Engaging stakeholders in tax policy discussions, including business leaders and economic experts, will ensure that the proposed tax measures foster growth without inadvertently triggering economic slowdowns.

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The Impact of Strategic Knowledge Management on Business Performance in Small and Medium Enterprises (SMEs)

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ABSTRACT

Strategic knowledge management is recognized as a fundamental pillar of organizational success in today's knowledge-driven era. This approach surpasses traditional information management by positioning knowledge as a strategic asset central to organizational decision-making. The primary objective of this study is to examine the effect of strategic knowledge management on business performance in small and medium-sized enterprises (SMEs) located in Ilam City. In terms of purpose, the research is applied, and methodologically, it adopts a descriptive-survey design. The statistical population of the study comprises 320 managers and experts from active SMEs in Ilam City. Based on Morgan's table and using a simple random sampling technique, a sample of 175 participants was selected. Standardized questionnaires were employed for data collection. The strategic knowledge management variable was measured using the instrument developed by Shaik et al. (2024), while business performance was assessed using the questionnaire developed by Depino-Besada et al. (2025). Content validity of the instruments was confirmed through expert evaluation, and reliability was tested using Cronbach's alpha coefficient. Data analysis was conducted using SPSS and LISREL software. The findings revealed that strategic knowledge management has a positive and statistically significant impact on the business performance of SMEs in Ilam. Moreover, it was found to have a significant positive influence on exports, innovation, and the expected growth of these enterprises.

KEYWORDS

Business Performance, Expected Growth, Exports, Innovation, Small and Medium Enterprises, Strategic Knowledge Management.

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Introduction

In the new era, knowledge plays a fundamental role as the driving force of individual and social progress and development. With the expansion of digital technologies and the explosion of information, access to knowledge has become unprecedentedly universal; however, the ability to analyze, synthesize, and apply it has become a determining factor in success (Zhang et al., 2025). Societies that prioritize investment in education, research, and innovation are not only pioneers in solving global challenges such as climate change and inequality but also they create greater economic welfare and social resilience. At the individual level, lifelong learning and cognitive flexibility are the keys to adaptation in today's dynamic and complex labor market. Therefore, knowledge in the twenty-first century is not only power but also a necessity for survival and growth in a highly interconnected world (Lim et al., 2025).

The identification of knowledge as a key factor, knowledge management activities, and the subjective nature of organizational knowledge assets, along with the long-term requirements of organizations, necessitate a different approach to knowledge management (Basit et al., 2024). Current thinking considers strategic knowledge management as an effective competitive tool to support organizational performance. Despite the existence of various knowledge management tools, organizational managers compete with each other to rapidly transform approaches to apply knowledge in the field of innovation. Therefore, focusing on strategic management has become essential because the emergence of knowledge innovation never stops and changes with competitive environments and new market conditions, depending on human data, decision-making, collaboration, creative reactions, strategy formulation, strategic knowledge, and knowledge-sharing structure (AlQershi et al., 2023).

Strategic knowledge management refers to the systematic process of identifying, storing, distributing, and applying knowledge in an organization to achieve long-term goals. In today's knowledge-based era, successful organizations are those that can effectively manage and transform the tacit and explicit knowledge of employees, customers, and partners into competitive advantage (Venkitachalam et al., 2022). The importance of this approach lies in preventing resource waste, enhancing efforts, and losing opportunities, helping organizations to act more intelligently in dynamic and complex environments (Hayaeian et al., 2022). Key applications of strategic knowledge management include improved decision-making, continuous innovation, and increased productivity (Lai et al., 2021).

In today's economy, where knowledge is considered as the most important intangible asset of organizations, strategic knowledge management is not a choice but a necessity for survival. Companies like Amazon and Tesla continuously update themselves by analyzing customer data and sharing knowledge between different departments. On the other hand, organizations that neglect the strategic knowledge management increase the risk of obsolescence, reduced flexibility, and loss of specialized personnel. Therefore, integrating knowledge management into organizational strategy is a way to ensure sustainable growth and competitiveness in the long term (Taghizadeh et al., 2021).

When properly and successfully implemented, strategic knowledge management strengthens business performance by optimizing organizational processes, enhancing innovation, and improving decision-making, directly impacting business performance. Organizations that systematically collect, analyze, and apply knowledge typically have higher productivity, lower operational costs, and faster response times (Ferreira et al., 2020). Additionally, strategic knowledge management facilitates organizational learning, prevents the repetition of past mistakes, and helps companies be more flexible when facing crises (Vătămănescu et al., 2020).

Given the importance of strategic knowledge management in organizations, and considering that improving business performance in small and medium enterprises is the main factor for survival and competitiveness of these companies, small and medium enterprises in Ilam city, due to their proximity to the international border with Iraq and their export opportunities, can improve their business performance. In this regard, the role of knowledge and innovation in these companies is of paramount importance. Considering that strategic knowledge management can improve knowledge and create innovation, this study seeks to investigate the impact of strategic knowledge management on business performance in small and medium enterprises in Ilam city.

Most studies on strategic knowledge management have focused on large companies, while SMEs, due to their specific characteristics (high agility, decentralized structure), and need different models in this area. The present research study has been conducted among small and medium exporting companies. The export performance of these companies plays a key role in economic growth, business development, and strengthening their competitive position. Small and medium exporting companies face unique challenges in international markets, including competition with larger competitors who have more financial resources and organizational knowledge, as well as dependence on knowledge management. These companies typically have limited resources, and strategic knowledge management can help them use existing knowledge to create a competitive advantage.

Literature Review

Knowledge Management

At a broad level, knowledge management refers to a collection of structured processes aimed at generating, distributing, and applying knowledge effectively (Harlow, 2018). It involves a systematic and integrated approach that combines suitable information technologies with human collaboration to identify, manage, and disseminate the knowledge assets of an organization. According to Najmi et al. (2018), knowledge management encompasses activities such as creation, acquisition, transformation, and application of knowledge. Its primary objective is to enable organizations to continuously respond and adapt to changes in external environments, including market dynamics, social developments, political factors, and evolving customer preferences (Secundo et al., 2019). Abbasi and Musakhani (2024) describe knowledge management as a process that assists organizations in identifying, organizing, and sharing critical information and competencies—often existing in a fragmented form—constituting part of the organizational memory. This process enhances the organization's ability to solve problems, learn, engage in strategic planning, and make informed, adaptive decisions. Furthermore, knowledge management places strong emphasis on codifying and representing knowledge in formats that facilitate formal sharing and repeated use (Claver-Cortés et al., 2018).

Strategic Knowledge Management

Since knowledge is considered as the most strategic organizational resource, organizations face the fundamental question of how they can efficiently and effectively manage organizational knowledge to benefit from its advantages in advancing organizational strategic objectives. Thus, establishing an efficient and effective knowledge management system as a key organizational competency in the new era, which can create sustainable competitive advantages, is essential (Laihonen & Mäntylä, 2018). A very fundamental and noteworthy point that leads to the emergence of a strategic approach in knowledge management is that knowledge management should serve the strategic movement of the organization and its strategic interaction with the turbulent and changing business environment. Knowledge and its management alone and independent of the organization's strategic objectives will be completely meaningless and worthless. Therefore, the organizational knowledge management should be aligned and coordinated with the organization's strategic actions at the macro level. Accordingly, the concept of strategic knowledge management (knowledge management with a strategic perspective) can be defined as knowledge management aligned with the strategic direction of the organization (Ngah & Wong, 2020). Based on Nonaka and Takeuchi's (1995) view, strategic knowledge management is the process of creating, transferring, and converting tacit and explicit knowledge in the organization. From Davenport and Prusak's (1998) perspective, this concept includes the processes of collecting, distributing, and using organizational knowledge effectively (Fernández-López et al., 2018). Strategic knowledge management enhances business productivity through strategic renewal (Sharafi & Hoseini, 2024). The concept of strategic knowledge management is based on several fundamental principles:

1. Knowledge as a strategic asset: In this view, knowledge is considered as the most important organizational asset that can create a sustainable competitive advantage.
2. Alignment of knowledge with organizational strategy: Knowledge management should not be separated from business objectives but should directly serve the fulfillment of the organization's mission.
3. Integrated knowledge processes: Including knowledge creation, acquisition, organization, storage, sharing, and application in a systematic manner.
4. Knowledge-oriented culture: Creating an environment in which continuous learning, innovation, and knowledge sharing are institutionalized as organizational values.

5. Knowledge-based technologies: Intelligent use of information systems as the technical foundation for knowledge management.
6. Measurement and evaluation: Assessing the impact of knowledge management on organizational performance through quantitative and qualitative indicators (Rasheed et al., 2025).

Business Performance

Business performance refers to the extent of an organization's success in achieving its strategic and operational objectives through the effective use of resources (human, financial, technological, and knowledge). This concept is a comprehensive criterion for measuring the effectiveness, efficiency, and sustainability of organizational activities in the long term (Masrizal et al., 2025). According to the traditional (financially-oriented) perspective, business performance is measured solely by financial indicators such as profitability, return on investment (ROI), market share, and cash flow (Depino-Besada et al., 2025). From a multidimensional perspective, performance includes non-financial dimensions such as customer satisfaction, product quality, innovation, employee satisfaction, and corporate social responsibility (CSR) (Trivedi et al., 2021). From a stakeholder perspective, successful performance creates a balance between the demands of shareholders, customers, employees, society, and the environment. From a process perspective, it focuses on the efficiency of internal processes (such as production, supply chain, and after-sales services) (Guerrero et al., 2019).

Strategic Knowledge Management and Business Performance

Knowledge, as the primary capital of organizations, has captured the management's attention and influenced the way operations are conducted. If knowledge management is established in organizations in a strategic and forward-looking manner, it will improve organizational performance at a faster rate (Cheng, 2020). With the expansion of strategic knowledge management, the risk of future unknown activities can be reduced. Having strategic knowledge management can provide organizations with a competitive advantage (Mehdikhani et al., 2019). The importance of strategic knowledge management is that it transforms knowledge from a passive asset into an active competitive advantage. In today's economy, where technological changes and market transformations occur at an unprecedented speed, successful organizations are those that can convert knowledge into practical solutions faster than competitors. Strategic knowledge management not only increases operational efficiency but also enables market leadership by encouraging innovation and creating new knowledge (Rialti et al., 2020). The impact of strategic knowledge management on business performance goes beyond short-term improvements and ensures the long-term sustainability of organizations. Businesses that integrate knowledge management into their strategy not only reduce the risk of losing specialized personnel and organizational knowledge but also gain the agility necessary to adapt to market changes (Hughes et al., 2021). In a world where knowledge is power, organizations lacking efficient knowledge management systems will gradually be eliminated from competition. Therefore, investing in strategic knowledge management today is not a choice but a necessary condition for survival and growth in digital age (Mata et al., 2024).

Hypothesis Development and Conceptual Framework

Strategic Knowledge Management and Business Performance

Strategic knowledge management today is not a choice but a necessity for survival in the turbulent business environments. Organizations that ignore this approach will quickly be eliminated from competition by knowledge-oriented competitors (Vătămănescu et al., 2020). Strategic knowledge management improves the organizational efficiency and effectiveness by reducing operational costs through documenting knowledge and optimizing organizational processes (Laihonen & Mäntylä, 2018). Organizations that pursue the implementation of strategic knowledge management and have coherent and precise planning in this regard have higher competitive power and more successful operational mechanisms compared to organizations that neglect this key issue (Rasheed et al., 2025). Harlow (2018) stated in his study that strategic knowledge management enhances the quality and effectiveness of organizations, creating a competitive advantage for organizations. It also improves performance at both individual and organizational levels. Najmi et al. (2018) stated that strategic knowledge management has a positive and significant impact on organizational performance responsiveness through dynamic capabilities. Secundo et al. (2019) argued that knowledge-based organizations improve their performance by integrating knowledge management and strategic management. Based on the above information, the following hypothesis is formed to be explored in the present research study:

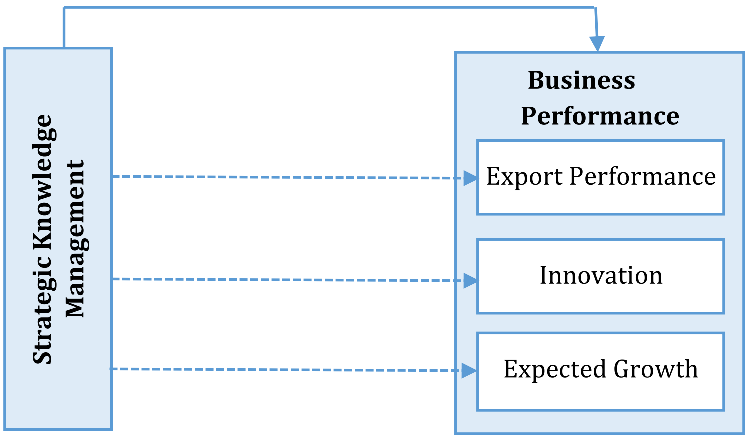
H1: Strategic knowledge management has a significant impact on business performance.

In a study by Shaik et al. (2024), strategic knowledge management was presented as a one-dimensional construct affecting the business performance. Additionally, Depino-Besada et al. (2025) stated that the performance of small and medium businesses consists of three components of export performance, innovation, and expected growth. Rasheed et al. (2025) also argued that strategic knowledge management affects the sustainable performance of the organization and its components. Therefore, the secondary research hypotheses, which examine the effect of strategic knowledge management on the components of business performance, are presented:

- **H1-1:** Strategic knowledge management has a significant impact on the export performance of businesses.
- **H1-2:** Strategic knowledge management has a significant impact on business innovation.
- **H1-3:** Strategic knowledge management has a significant impact on the expected growth of businesses.

Based on the mentioned points, the conceptual model of the present study is depicted in Figure 1.

Figure 1.
The Conceptual Research Model



(Source: Adapted from Shaik et al. (2024) and Depino-Besada et al. (2025))

Methodology

This study is classified as applied research in terms of its objective. Methodologically, it is categorized as a descriptive-survey research study. The statistical population of the study consists of 320 managers and specialists from active small and medium-sized enterprises (SMEs) in Ilam city. Using Morgan's sampling table and a simple random sampling technique, 175 individuals were initially selected. After the distribution and collection of the questionnaires, a total of 165 were deemed valid and usable for analysis.

Data collection methods in this study comprised both field and library-based approaches. The field method was employed to gather empirical data necessary for addressing the research questions, while the library method—encompassing the review of books, scholarly articles, journals, prior research studies, and online academic databases—was utilized to construct the theoretical framework and literature review.

The primary instrument for data collection was a standardized questionnaire. The structure of the questionnaire, including the items corresponding to each variable and the researchers from whom the instruments were adopted, is summarized in Table 1.

Table 1.
Questionnaire Items

Variable	Dimensions	Number of Questions	Source
Business Performance	Export Performance	4	Depino-Besada et al. (2025)
	Innovation	4	
	Expected Growth	4	
Strategic Knowledge Management	----------	12	Shaik et al. (2024)
Total Questionnaire	----------	24	

(Source: Researcher's Findings)

To evaluate the validity of the questionnaire, expert judgment and input from academic faculty members specializing in the relevant field were employed, confirming the content validity of the questionnaire. To assess the content validity quantitatively, two statistical measures were utilized: the Content Validity Ratio (CVR) and the Content Validity Index (CVI). The CVR score was calculated at 0.84, exceeding the minimum acceptable threshold of 0.62, thereby confirming the content validity of the item. Furthermore, the CVI was determined to be 0.88, which surpasses the standard benchmark of 0.79, providing additional evidence supporting the content validity of the instrument. To determine the reliability of the questionnaire, Cronbach's alpha coefficient was computed. The resulting alpha value of 0.93 indicates a high level of internal consistency, affirming that the questionnaire possesses strong reliability.

Table 2.
Cronbach's Alpha Coefficient for Research Variables

Variable	Cronbach's Alpha Coefficient
Strategic Knowledge Management	0.89
Export Performance	0.82
Innovation	0.90
Expected Growth	0.92
Total Questionnaire	0.93

(Source: Researcher's Findings)

Structural Equation Modeling was used with LISREL software to analyze the data.

Findings

In this section, first, the normality of the data is examined by running the Kolmogorov-Smirnov test. Then, appropriate tests are used to test each hypothesis.

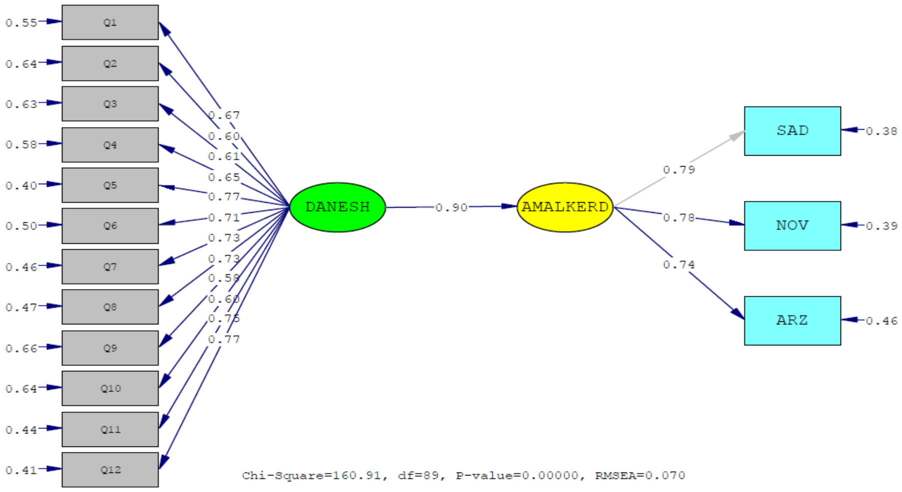
Table 3.
Normality Test of the Research Variables

Variables	Number of Items	Significance Level	Z Statistic	Result
Strategic Knowledge Management	12	0.73	0.89	Data distribution is normal
Export Performance	4	0.58	0.76	Data distribution is normal
Innovation	4	0.81	0.93	Data distribution is normal
Expected Growth	4	0.69	0.88	Data distribution is normal

(Source: Researcher's Findings)

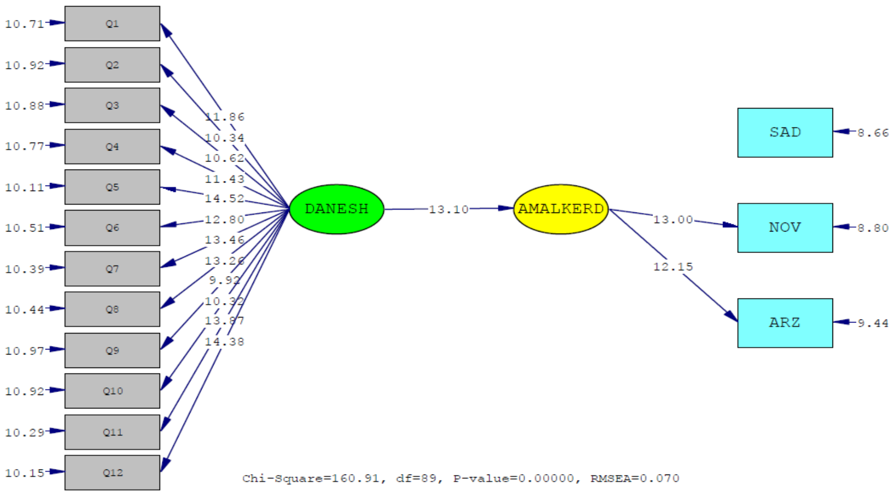
As shown in the above table, the significance levels for all variables exceed the 0.05 threshold, indicating that the data follow a normal distribution. To evaluate the main hypothesis of the study, the Structural Equation Modeling (SEM) approach was employed using LISREL software. Two distinct models were utilized in this research to test both the primary hypothesis and the associated sub-hypotheses.

Figure 2.
The Structural Model of the Main Research Hypothesis in Standard Estimation Mode



(Source: Researcher's Findings)

Figure 3.
The Structural Model of the Main Research Hypothesis in Significance Coefficient Mode



(Source: Researcher's Findings)

To evaluate the model fit, specific indices are used. Table 4 presents the calculated values of these indices compared to their permissible values, with results indicating an optimal fit of the model.

Table 4.
A Comparison of the Fit Indices for the Structural Model of the Main Hypothesis

Indices	Permissible Value	Calculated Coefficients for the Main Research Model	Result
GFI	Above 0.9	0.93	Good fit
AGFI	Above 0.9	0.99	Good fit
RMR	Closer to zero is better	0.03	Good fit
NFI	Above 0.9	0.90	Good fit
IFI	Above 0.9	0.92	Good fit

(Source: Researcher's Findings)

According to widely accepted guidelines, the adequacy of the default (fitted) model is confirmed when the estimated fit indices presented in Table 4 fall within the acceptable thresholds. Conversely, if these coefficients lie outside the defined range, it suggests a poor model fit. Table 4 presents the status of the fit indices for the structural model related to the main hypothesis. A comparison between the column of estimated coefficients and the column indicating acceptable ranges reveals that the model exhibits an acceptable level of fit.

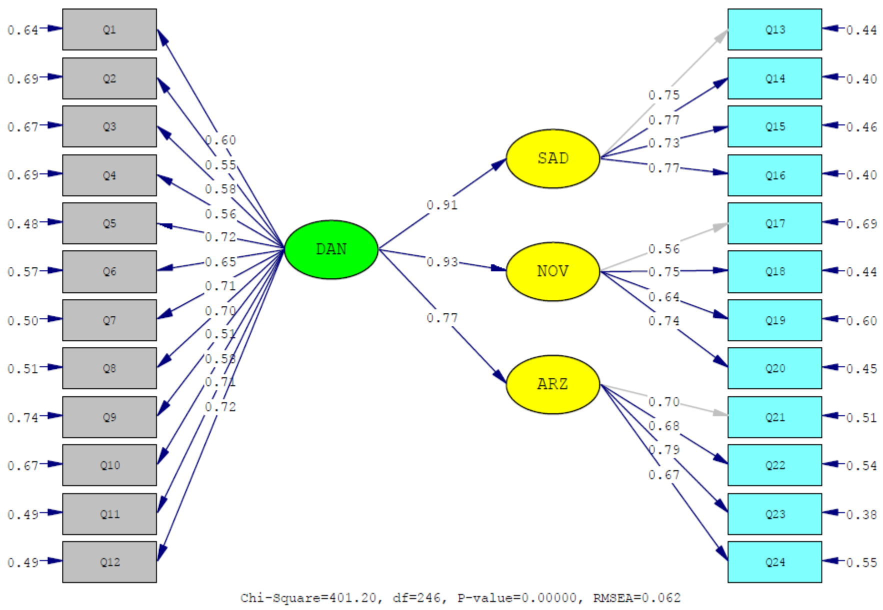
Table 5.
The Results of the Main Research Hypothesis

Standard Coefficient	T-value	Independent Variable	Dependent Variable	Test Result
0.90	13.10	Strategic Knowledge Management	Business Performance	Confirmed

(Source: Researcher's Findings)

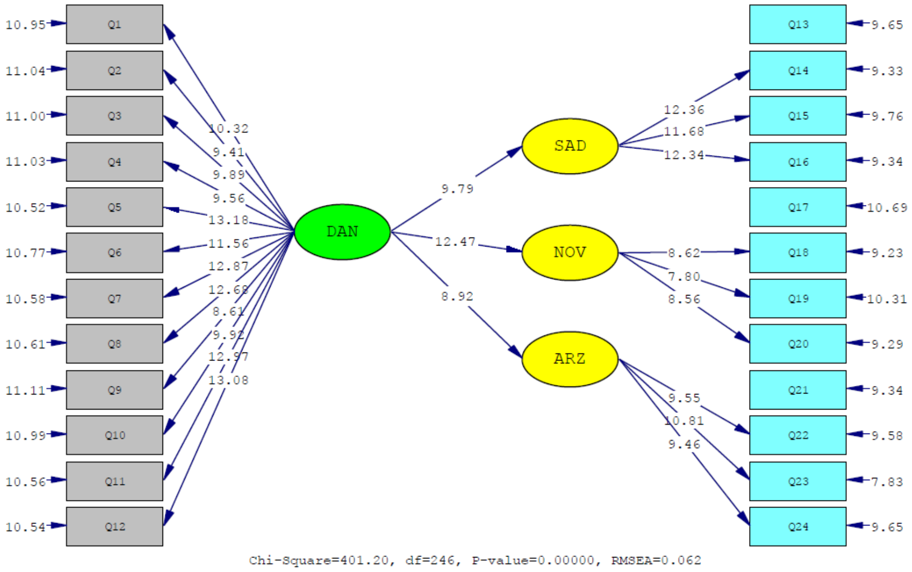
The primary hypothesis posits that strategic knowledge management significantly influences the business performance of small and medium-sized enterprises (SMEs) in Ilam city. As shown in Table 5, the standardized path coefficient between strategic knowledge management and business performance is 0.90. Furthermore, the corresponding t-value is 13.10, which exceeds the critical threshold of 1.96, thereby confirming the hypothesis. Consequently, it can be concluded that strategic knowledge management exerts a direct, positive, and statistically significant effect on the business performance of SMEs in Ilam city. Therefore, the main research hypothesis is supported.

Figure 4.
The Structural Model of the Secondary Research Hypotheses in Standard Estimation Mode



(Source: Researcher's Findings)

Figure 5.
The Structural Model of the Secondary Research Hypotheses in Significance Coefficient Mode



(Source: Researcher's Findings)

The results of examining the goodness of fit for the structural model of the secondary research hypotheses are reported in Table 6.

Table 6.
A Comparison of the Fit Indices for the Structural Model of the Secondary Research Hypotheses

Indices	Permissible Value	Calculated Coefficients for the Secondary Hypotheses Model	Result
GFI	Above 0.9	0.91	Good fit
AGFI	Above 0.9	0.93	Good fit
RMR	Closer to zero is better	0.06	Good fit
NFI	Above 0.9	0.99	Good fit
IFI	Above 0.9	0.94	Good fit

(Source: Researcher's Findings)

As observed, the status of indices for the structural models of the secondary research hypotheses is shown in Table 6. The comparison of the calculated coefficients column with the permissible range column indicates that the model fit indices are appropriate.

Table 7.
The Results of the Secondary Research Hypotheses

Standard Coefficient	T-value	Independent Variable	Dependent Variable	Test Result
0.91	9.79	Strategic Knowledge Management	Export Performance	Confirmed
0.93	12.47	Strategic Knowledge Management	Innovation	Confirmed
0.77	892	Strategic Knowledge Management	Expected Growth	Confirmed

(Source: Researcher's Findings)

According to Table 7, the significance values for all three secondary research hypotheses are greater than 1.96, and the effect coefficients between all three research variables are positive. Therefore, it can be concluded that strategic knowledge management has a positive and significant impact on exports, innovation, and expected growth.

Discussion and Conclusion

In today's knowledge-driven economy, knowledge serves as the primary catalyst for growth. Organizations that effectively manage knowledge strategically are the ones that maintain their competitive edge. Strategic knowledge management acts as a vital link between "what an organization knows" and "what it is capable of achieving", and failing to prioritize it means missing numerous opportunities for progress. Organizations that successfully implement strategic knowledge management play a pivotal role in gaining a competitive advantage and enhancing the overall organizational performance.

The primary aim of this study was to explore the impact of strategic knowledge management on business performance. Drawing upon theoretical foundations and the proposed conceptual model, four hypotheses (one main hypothesis and three sub-hypotheses) were formulated. After gathering the data using standardized questionnaires and analyzing the results with LISREL software, the findings revealed that strategic knowledge management positively and significantly influences business performance, as well as its key dimensions, including export performance, innovation, and anticipated growth.

The results obtained from the present research study directly and indirectly align with the findings of researchers such as Harlow (2018), Najmi et al. (2018), Secundo et al. (2019), Ngah et al. (2020), Rialti et al. (2020), Trivedi et al. (2021), Hayaeian et al. (2022), Basit et al. (2024), Shaik et al. (2024), and Rasheed et al. (2025), among others.

Given the positive and significant impact of strategic knowledge management on business performance of small and medium enterprises in Ilam city, the following recommendations are suggested:

- It is recommended that small and medium businesses establish an integrated knowledge management system in their company. In this regard, they can implement digital platforms such as organizational wikis, cloud document systems, and intelligent knowledge bases.
- It is recommended that a knowledge-sharing culture be created in companies. In this regard, they can develop incentive programs for knowledge sharing (such as reward systems), hold regular knowledge enhancement meetings between departments, and create internal social networks.
- It is recommended that knowledge management be aligned with business strategies. In this regard, it is suggested that businesses take actions such as creating the role of Chief Knowledge Officer, developing organizational knowledge strategy, and linking the reward system with knowledge objectives.

- It is recommended that managers of small and medium enterprises implement strategic knowledge management, establish a knowledge base to create an atmosphere of trust and create a knowledge creation working group to minimize the role of biases and secondary experiences in profitability results.

Managerial Implications: Managers of small and medium businesses can use the results of this study in a practical and applied manner to improve the performance of their organizations. By establishing and implementing strategic knowledge management, while transforming knowledge into tangible competitive advantage and improving strategic decision-making in the organization, they can achieve sustainable competitive advantages and improve their business performance.

Theoretical Innovation: The general conclusion of the present study indicates that strategic knowledge management, as one of the factors influencing competitive power and creating competitive advantage, and ultimately improving business performance, plays a key role in exporting small and medium enterprises. In previous research on strategic knowledge management, it has mostly been studied in large organizations or companies. The focus of the present study has been on exporting small and medium enterprises.

Limitations: There are some limitations in the present study. Although the data of this study support the proposed model, the first limitation of this research is related to the spatial domain of the research. This study was conducted in Iran among small and medium enterprises in Ilam city. Given the different economic, political, and cultural factors of countries and their major role in the performance of export businesses, to generalize the model, it is recommended that similar studies be conducted to confirm the extracted model in different countries. The second limitation is that these results may change in other industries. Therefore, it is recommended that these relationships be compared across different industries.

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