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From the Editor

Dear Readers,

It is my great privilege to welcome you to this new issue of the Journal of Information and Organizational Sciences (JIOS) as its newly appointed Editor-in-Chief. As a full professor at the Faculty of Organization and Informatics, I am honored to take the helm of this esteemed journal and guide it through its next phase of growth and development. To support this vision, we have refreshed the Editorial Board, bringing together accomplished scholars committed to enhancing the journal's quality and impact.

This issue also marks the debut of JIOS's new visual identity, symbolizing our renewed dedication to innovation, clarity, and accessibility. Beyond aesthetics, we are introducing significant operational improvements, focusing on reducing manuscript review times while maintaining our rigorous academic standards. These efforts aim to attract and publish high-quality research across the diverse domains JIOS covers.

Our commitment to open access remains a cornerstone of our mission. JIOS continues to be an inclusive platform that ensures all published work is freely accessible to readers worldwide, with no fees for authors. We firmly believe in the power of knowledge sharing without financial barriers.

This issue features a diverse and impactful collection of articles addressing cutting-edge topics. Those involve advanced predictive models for public health and financial markets, innovative machine learning and natural language processing approaches for sentiment analysis and cybersecurity, and algorithmic methods for modeling online information diffusion. They also explore organizational factors such as culture, trust, and HR practices that influence technology adoption, sustainability, innovation, and task performance in workplace environments. Additionally, this issue highlights trends in educational management and blended learning, offering scientometric insights into this evolving field. Together, these studies contribute to advancements in information systems, organizational sciences, and applied machine learning.

We hope you find these contributions both insightful and inspiring. Thank you for your continued interest in JIOS, and we look forward to your engagement as readers, authors, and reviewers. Together, we can advance knowledge and make meaningful contributions to our fields.

Sincerely,

Prof. Igor Balaban, Ph.D.
Editor-in-Chief
Journal of Information and Organizational Sciences

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Original Scientific Paper

Deep Learning Model for Predicting Spreading Rates of Pandemics, "COVID-19 as Case Study"

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ABSTRACT

The outbreak of Coronavirus (COVD-19), has led to a catastrophic scenario over the globe, causing the cumulative prevalence of this virus to increase dramatically day by day. Both Machine learning (ML) and deep learning (DL) provide great chances to facilitate tracking disease, anticipating increase in pandemic, and hence planning for coverage techniques to control its spread. This work is based on the application of an advanced mathematical model to examine and predict the increase in a pandemic. On the bases of time-series data, an advanced DL model has been implemented to predict the risk of COVID-19 spreading in Iraq. A hybrid approach is presented where two deep learning algorithms; LSTM and GRU are brought up together to achieve good prediction with rewarding levels of (MAE = 0.109), (MAPE = 0.191) and (RMSE = 0.134).

Keywords: Pandemic, COVID-19, Coronavirus, Machine Learning, Deep Learning, Outbreak prediction

1. Introduction

The first case of coronavirus disease (CoVID-19) was first detected and acknowledged on December the 31, 2019, in Wuhan, China. It began to spread fast all over the world [1]. Accumulative occurrence of causative virus (SARS - CoV-2) is hastily growing and has severely affected about 196 nations and countries within USA and Europe [2]. Since then, the World Health Organization (WHO) has classified the coronavirus outbreak as a pandemic, while the virus continues to spread [3]. The distinction between the pandemic instigated by CoV-2 and other associated viruses, such as SARS and MERS, lies in CoV-2's capacity to spread rapidly through human interactions, resulting in nearly 20% of infected individuals remaining asymptomatic carriers [4]. Additionally, various studies have confirmed that diseases caused by CoV-2 pose a significantly greater risk for individuals with compromised immune systems. Furthermore, older adults and patients with life-threatening chronic like coronary cardiopathy, HIV, AIDS and others, are more likely to severe effects [5]. Due to absence of cure medicine, the only way afforded to control and slow down the spreading was practicing distancing in society and following health guidelines to break the transmission chain of the virus. This manner of behavior of CoV-2 necessitates the need for an increasingly robust mathematical basis for tracking its exposure and automates monitoring equipment to perform online dynamic selection.

There is a need for innovative and rapid solutions that allow for developing, managing, and analyses of big data related to the grown-up network of infected individuals, details of patients, community movearounds, and combination with clinical institutions' trials, genetic and general fitness information [6]. The availability of multiple data sources, such as text messages, social media interactions, online communications, and various articles on the web, enabled a thorough analysis of infection growth in relation to community behavior or through sampling methods. Wrapping this data with ML, DL and divers Artificial Intelligence (AI) and data science techniques, researchers can manage providing the needful prediction of regions and time likely for the disease to propagate, and to report those regions, as a consequent, to assist the needful authorities' arrangements. A method to examine epidemiological correlations with disease propagation behavior involves the automatic tracking of the travel history of infected individuals.

Some of communities' transportation-based effects have been discussed in a number of researches. For the huge amount of data, necessitates careful consideration of the infrastructure required for its storage and analysis, ensuring that development proceeds in an efficient and cost-effective way. This necessitates the establishment of solutions grounded in deep learning and artificial intelligence methodologies [7]. Various pneumonia types were addressed through machine learning and deep learning techniques for CT image analysis, offering valuable support to CoVID-19 patients [8]. Further related insights can be found in [9]. Moreover, the discovery of vaccine for CoVID-19 can further be elevated via analysis of genome sequences, using numerous ML, DL and other AI techniques [10].

2. Motivation and Contributions

This work concerns predicting spread rate of CoVID-19 in Iraq. Time-series dataset used are obtained from WHO – published global datasets to develop a novel forecasting model for CoVID-19 outbreak. Data-driven estimations and time-series data – based analysis is incorporated to predict the trends of virus dynamics in a range of up to come days such as confirmed positive cases, number of deaths, number of recovered cases and others that hopefully beneficiate governments, medical institutions and even citizens to respond proactively and take the necessary precautions to avoid outbreaks. To achieve the estimations, deep learning algorithms of Long-Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) are suggested to model with, both in a combination, in an aim to gain the best prediction that effectively support governing such health threat crises.

3. Related Work

Development of the novel models for time-series prediction of Coronavirus (COVID-19) is of maximum importance. Machine learning (ML) methods have recently shown promising results. The present study aims to engage an artificial neural network (ANN) integrated by grey wolf optimizer (GWO)for Coronavirus (COVID-19) outbreak predictions by employing the Global dataset [14]. In this paper, the Coronavirus (COVID-19) outbreak is modelled as a complex time series. We have developed a hybrid Machine Learning (ML) model based on the artificial neural network (ANN). We trained the system with the grey wolf optimization (GWO) algorithm to get the highest performance. Based on the testing, we projected the outbreak until late May [14].

In this paper, the exact structure of Res Net-a hundred and is first prepared [15]. Education began for several hours. The unique information of R registration slips was manually collected to reap advanced results. Predicting the status of the viral load is designed to accurately reach the target area suitable for strict standard operating procedures, to reduce COVID-19. Attention parameters were the calculation of accuracy, precision and recall. Moreover, the hourly surrogate viral load was manipulated from October 15, 2020 to November 1, 2020. On November 3, the prediction was determined by the skilled Res Net-a hundred and one, and the accuracy became very close [15]. Secondly, Covid-19 was predicted by chest X-ray, but to save time for researcher destiny, 3 new technical frameworks were compared with R-CNN, Mask R-CNN and ResNet-50. Manipulation has become based entirely on precision, accuracy, and recall. The faster R-CNN does well compared to the Mask R-CNN and ResNet-50. The error framework is designed to test the amount of error after which it is reduced through classification techniques. The most important reason for these studies has become to make it less difficult for growing international sites that do not have a vaccination facility for contamination with the virus, and to allow time for rapid treatment of Covid-19 patients [15].

This paper aims to evaluate the currently advanced structures primarily based totally on deep studying strategies the usage of special clinical imaging modalities like Computer Tomography (CT) and X-ray [16]. This evaluate mainly discusses the structures advanced for COVID-19 prognosis the usage of deep studying strategies and affords insights on famous records units used to educate those networks. It additionally highlights the records partitioning strategies and numerous overall performance measures advanced with the aid of using researchers on this field. A taxonomy is interested in categorize the current works for correct insight. Finally, we finish with the aid of using addressing the demanding situations related to using deep studying strategies for COVID-19 detection and likely destiny developments on this studies area. The goal of this paper is to facilitate experts (clinical or otherwise) and technicians in know-how the methods deep studying strategies are used on this regard and the way they may be doubtlessly in addition applied to fight the outbreak of COVID-19[16].

COVID-19, commonly referred to as coronavirus disease, is an infectious disease caused by the new coronavirus. Detection of coronavirus currently depends on elements such as patients' signs and symptoms, where the individual lives, visited records and close contact with any coronavirus patients. In order to screen a COVID-19 patient, the health care issuer uses an elongated swab to take a nasal pattern. The pattern is then examined in a laboratory setting. If an individual coughs, saliva (sputum) is released for examination. Prognosis will become more important while there may be loss of reagents or capacity verification, virus monitoring and severity, and communication with massive COVID-19 patients via the means of a healthcare practitioner. In this case of COVID-19 pandemic, streaming prediction based entirely on retrospective examination of laboratory facts in the form of chest x-rays using deep learning may be required [17].

This paper proposed a demystification method for locating COVID-19 using scientific pixel clustering with the help of deep networks. Study reports promising effects with 91.67% accuracy for diagnosis COVID-19 and 100 Score in Proven Survival Ratio [17].

4. Materials and Methods

4.1. Deep Learning Models

Techniques based on deep learning have shown significant performance increases in a variety of applications reported in the literature. This section provides a brief overview of the fundamental principles of deep learning models used to predict spreading rate of COVID-19 on the bases of time series data gathered from WHO concerning COVID-19 in Iraq for a period of about 2 months started at February the 4th of 2020 using a hybrid approach combining together LSTM and GRU.

4.1.1. LSTM Models

The LSTM [18] introduced a gated memory unit to address the vanishing gradient issues that constrain the performance of a standard RNN [19]. At a critical time step, the gradient either diminishes excessively or escalates dramatically resulting in a vanishing gradient problem. This issue appears consistently during the training process, as the optimizer's return propagation leads to the technique executing, even though the weights hardly alternate anymore. Basically, LSTM is composed of three gates. The three gates—input, forge, and output—serve to regulate the flow of information. These gates are fundamentally constructed using logistic functions derived from weighted sums, with the weights being obtainable during the training process through back propagation. The input and forget gates control the cell state. The output is generated by the output gate or the hidden state, which signifies the memory allocated for utilization. This method allows the network to maintain information for an extended period, a capability that conventional single RNNs do not possess. Indeed, the beneficial features of LSTM include their improved ability to capture long-term dependencies and their remarkable skill in handling time-series data.

Considering an input time-series sample Xt, along with the specified number of hidden units h, the equations governing the gates are as follows:

- Input Gate: $It = \sigma (X t W xi + Ht-1 W hi + bi)$, … (1)
- Forget Gate: $Ft = \sigma (X t W x f + Ht-1 W h f + bf)$, … (2)
- Output Gate: $O t = \sigma (X t W xo + Ht-1 W h o + b o)$, …(3)
- Intermediate Cell State: $\tilde{C} t = \tan h (X t W x c + H t-1 W h c + b c)$,…(4)
- Cell State (next memory input) $Ct = Ft \circ C t-1 \circ \tilde{C} t$, …(5)
- New State: $H t = O t \circ \tan h (C t)$, …(6)

where

- W x i , W x f , W x o and W h c , W h f , W h o refer respectively to the weight parameters and bi, bf , bo denote bias parameters.
- W x c , W h c denote weight parameters, b c is prejudice parameter, o reference to the element-wise multiplication. The assessment of Ct depends on the output information’s from memory cells (C t−1) and the current time step $\tilde{C}$ t.

4.1.2. GRU Models

GRU serves as another option to LSTM, introduced in [20], aimed at enhancing the performance of LSTM, decreasing parameters, and simplifying architecture. In GRU, the input gates and the forget gates of LSTM model are integrated into a single gate namely, the update gate (Figure 1). In contrast to LSTM, which has three gates, GRU has only two gates: update gate and reset gate. GRUs models bring new benefits such as the proposal of reset and update gate concepts. Finally, we present a new appreciation approach that enables the computation of hidden states in RNN models. The GRU enhanced the LSTM architecture by connecting the input and forget gates of the LSTM to the update gate, while utilizing the output gate as a reset gate. The update gate regulates the extent of previously retained memory, while the reset gate facilitates the integration of current inputs with prior memory. The mathematical relationships among the different components of the GRU are outlined as follows:

- Update gate: $Z_t = \sigma(X_t W_{xz} + H_{t-1} W_{hz} + b_z)$,...(7)
- Reset gate: $R_t = \sigma(X_t W_{xr} + H_{t-1} W_{hr} + b_r)$,....(8)
- Cell state: $\hat{H}_t = \tanh(X_t W_{xh} + (R_t \circ H_{t-1}) W_{hh} + b_h)$,
- New state: $H_t = Z_t \circ H_{t-1} + (1 - Z_t) \circ \hat{H}_t$,

where

- W_{xr}, W_{xz} and W_{hr} are weight parameters and b_r, b_z are bias parameters
- W_{xh}, W_{hh} are weight parameters, while b_h is a bias parameter. For a given time step t, the current update gate Z_t is utilized to combine the prior hidden state H_{t-1} and current candidate hidden state $\hat{H}_t$.

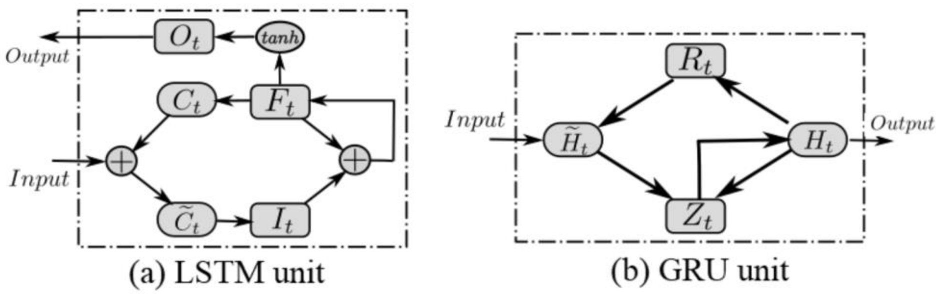

Figure 1. The basic structure of LSTM and GRU models. (a) It, Ft, and O t represent the three LSTM gates (input, forget and output gates respectively), C and ˜ C represent the candidate memory cells and memory cell content. (b) R t and Z t are reset gate and update gates respectively, H t and ˜H t is the candidate hidden state and hidden state respectively.

4.2. Evaluation Metrics

Generally speaking, the following indexes were used to evaluate ANN-based prediction models:

1. $RMSE = \sqrt{\frac{1}{n}} \sum_{t=1}^{n} (yt - \hat{y}t)^2$
2. $MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \%$
3. $MAE = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{n}$

In this context, (y t) represents the actual values, (ŷ t) denotes the expected values, and (n) indicates the total number of measurements taken. The RMSE indicator was selected due to its widespread application in assessing model quality within regression contexts and its role as a scoring metric in numerous data science competitions. Essentially, it is calculated using the logarithmic scale. The benefit of employing RMSE as a statistical measure lies in its strong resistance to outliers. Lower MAE or MAPE values approaching 1 signify improved predictive accuracy. Furthermore, we will examine the distribution of forecasting errors through the use of histograms.

4.3. Deep Learning-based COVID-19 Prediction

As stated, this work presents a DL architecture for predicting CoVID-19's spreading rate in Iraq. The proposed approach uses deep learning models to predict, on daily bases, confirmed positive cases, death cases and recovered cases. Figure 2 shows the general structure for the suggested prediction technique. The prediction of CoVID-19 has been accomplished via a two-phase process: training phase and testing phase. Initially, the raw data undergoes pre-processing and standardization prior to its application in constructing the DL model. Parameters in DL models are selected to assure minimization of the loss function throughout training process. Adam optimizer is employed for this task. During the testing phase, the models generated earlier with the parameters just selected are employed to predict the spreading rate of CoVID-19. This prediction functions based on the WHO's most effective tracking data, as for instant, the number of newly confirmed positive cases on day $t+1$, which relies on the corresponding cases recorded for specific previous days leading up to day t.

5. Results

5.1. Data Description

WHO has declared CoVID-19 in around 210 countries and territories globally. Most countries around the globe are currently facing the rapid and extensive propagation of the CoVID-19 outbreak. Extensive air traffic among nations participated badly in the spread of CoVID-19 from origin to various impacted regions; documented instances of person-to-person transmission have also occurred among close contacts of returning passengers. As stated earlier, the goal of this work is to predict CoVID 19's spreading and the consequent propagation of the pandemic. This work considers the number of confirmed daily registered cases and the recovered daily registered cases and other related data gathered and registered by the WHO in Iraq.

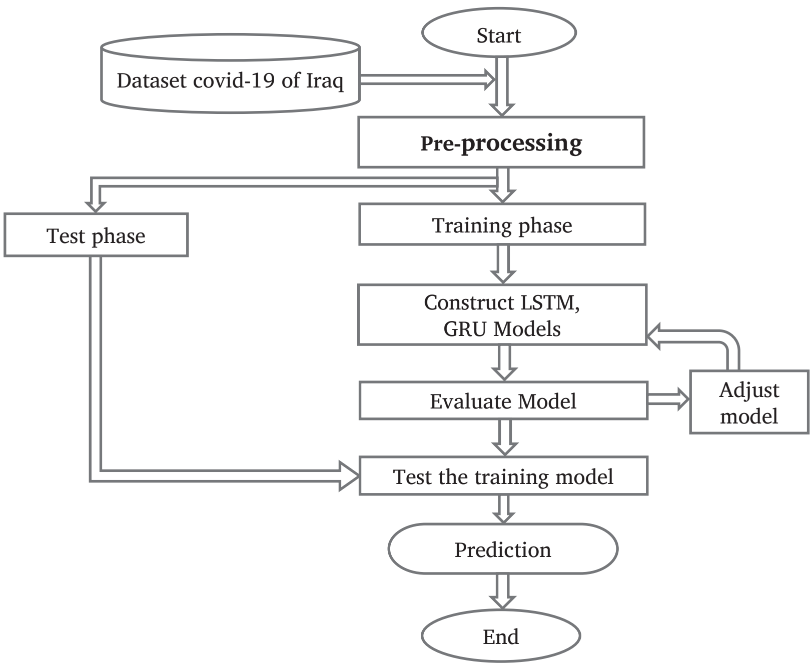

Figure 2. Conceptual underpinning for the proposed prediction algorithms

5.2. Data Analysis and Modeling

Descriptive data, as presented in Table 1, are considered as the descriptive coefficients that summarize a particular data set, which can either represent the overall or a sample pattern of population. It is necessary to examine the data before building a model as this assist getting maximum insights from the data, and to derive hypotheses that could possibly lead to experiment data using statistical graphs or other visualization techniques. Figure (3) depict aspects of applying such analysis to the leftover of the WHO dataset in Iraq.

Out[10]:

	count	mean	std \
total_cases	404.0	3.151048e+05	2.781007e+05
new_cases	404.0	2.135696e+03	1.717129e+03
new_cases_smoothed	404.0	2.117011e+03	1.643019e+03
total_deaths	404.0	7.244322e+03	5.362604e+03
new_deaths	404.0	3.624257e+01	3.180915e+01
new_deaths_smoothed	404.0	3.567608e+01	3.159147e+01
total_cases_per_million	404.0	7.834042e+03	6.914056e+03
new_cases_per_million	404.0	5.309703e+01	4.269077e+01
new_cases_smoothed_per_million	404.0	5.263250e+01	4.084823e+01
total_deaths_per_million	404.0	1.801062e+02	1.333235e+02
new_deaths_per_million	404.0	9.010668e-01	7.908473e-01
new_deaths_smoothed_per_million	404.0	8.870000e-01	7.854196e-01
reproduction_rate	404.0	1.118020e+00	2.414576e-01
total_tests	404.0	2.578967e+06	2.015761e+06
total_tests_per_thousand	404.0	6.411742e+01	5.011526e+01
new_tests_smoothed	404.0	2.201458e+04	1.155131e+04
new_tests_smoothed_per_thousand	404.0	5.473837e-01	2.871645e-01
positive_rate	404.0	1.118936e-01	6.486991e-02
tests_per_case	404.0	1.802104e+01	1.941576e+01
stringency_index	404.0	7.283342e+01	1.842463e+01
population	404.0	4.022250e+07	0.000000e+00
population_density	404.0	8.812500e+01	0.000000e+00
median_age	404.0	2.000000e+01	0.000000e+00
aged_65_older	404.0	3.186000e+00	4.891038e-15
aged_70_older	404.0	1.957000e+00	5.780318e-15
gdp_per_capita	404.0	1.566399e+04	1.293084e-10
extreme_poverty	404.0	2.500000e+00	0.000000e+00
cardiovasc_death_rate	404.0	2.186120e+02	1.138278e-12
diabetes_prevalence	404.0	8.830000e+00	4.624254e-14
handwashing_facilities	404.0	9.457600e+01	3.414834e-13
hospital_beds_per_thousand	404.0	1.400000e+00	1.067136e-14
life_expectancy	404.0	7.060000e+01	4.695397e-13
human_development_index	404.0	6.740000e-01	3.223639e-15

	min	25%	50% \
total_cases	1.000000e+00	8.672000e+03	2.885435e+05
new_cases	0.000000e+00	5.957500e+02	2.061500e+03
new_cases_smoothed	1.857000e+00	7.396430e+02	2.118143e+03

Table 1. Summary of COVID-19 of IRAQ Datasets

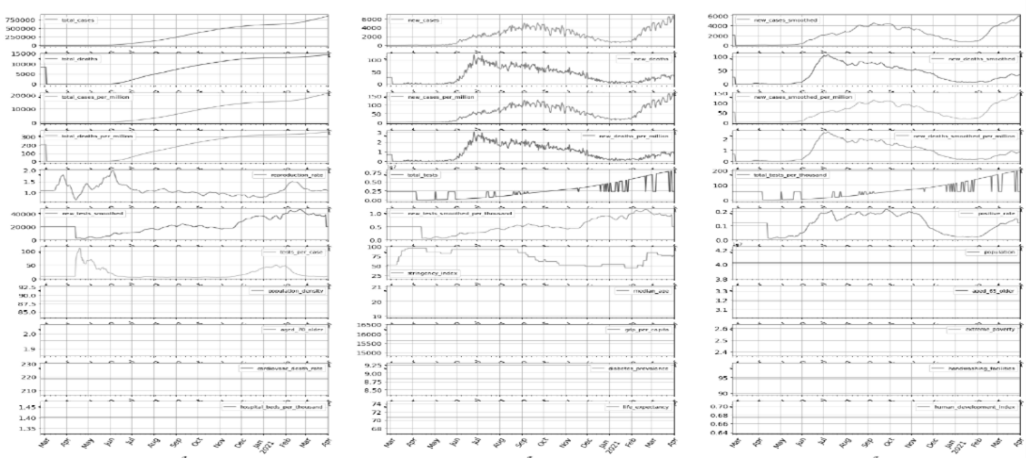

Figure 3. Visualization of Time-Series Data Analysis

5.3. Prediction over Time-Series Data

For the prediction over time series data, the model has to estimate the output, at certain point in time, as a function of the input over a certain range of preceding time points. So, to predict the output at time point t (that is x(t)), model should consider x (t - 1). In this sense, time series data, for a duration of time ranging 1-n, should be manipulated such that output samples at time {t, t + 1, ..., t + n} should be predicted out of input samples at time {t -n, t - n-1, ..., t -1}.

```
                    1         2         3         4         5
var1(t-1)    0.000000  0.000000  0.000005  0.000007  0.000007
var2(t-1)    0.000150  0.000000  0.000600  0.000300  0.000000
var3(t-1)    0.354241  0.354241  0.354241  0.354241  0.354241
var4(t-1)    0.578955  0.578955  0.578955  0.578955  0.578955
var5(t-1)    0.229508  0.229508  0.229508  0.229508  0.229508
...               ...       ...       ...       ...       ...
var29(t)     0.000000  0.000000  0.000000  0.000000  0.000000
var30(t)     0.000000  0.000000  0.000000  0.000000  0.000000
var31(t)     0.000000  0.000000  0.000000  0.000000  0.000000
var32(t)     0.000000  0.000000  0.000000  0.000000  0.000000
var33(t)     0.000000  0.000000  0.000000  0.000000  0.000000

[66 rows x 5 columns]
No of Features of cleandData:  33
No of Features of Reframed Date:  66
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5.4. Model Training

Figure 4 presents the behavior of the deep networks of LSTM and GRU, in terms of the model loss according to WHO Iraq time-series data.

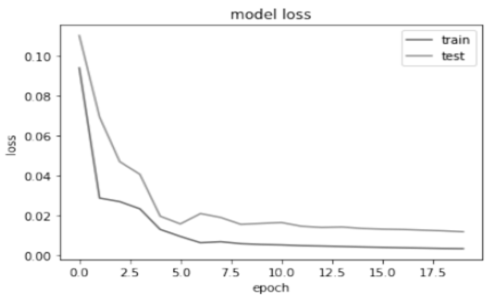

Figure 4. Training Model

5.5. Calculate Errors

This is done according to the error rate of the model:

Test MAE for LSTM: 0.109
Test MAPE for LSTM: 0.191
Test RMSE for LSTM: 0.134
Training elapsed Time: 11.428 Seconds

5.6. Model Testing

Figure 5 depicts testing model's prediction for the overall 33 features over 20% of the data that covers the time from 12/1/2021 to 2/4/2021, amongst is the prediction results for a two of the most vital features of "total-cases- per-million" and "new-confirmed-cases" as presented in Figure 6 and Figure 7 respectively.

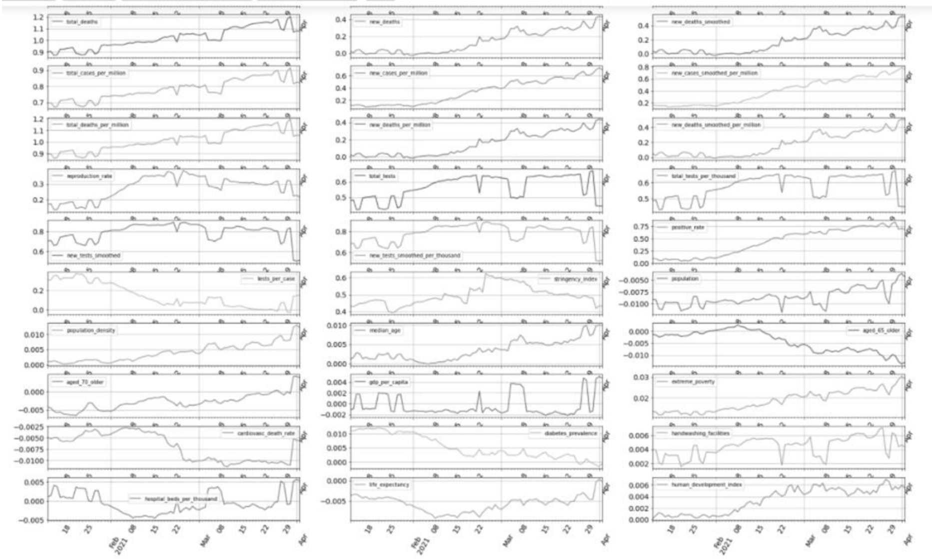

Figure 5. Testing model

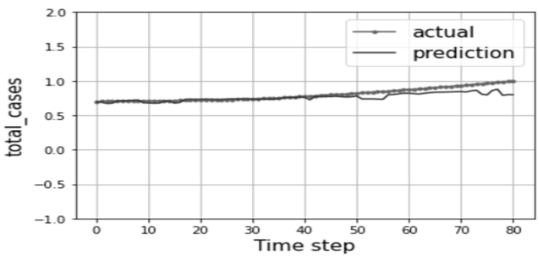

Figure 6. Total Cases per Million

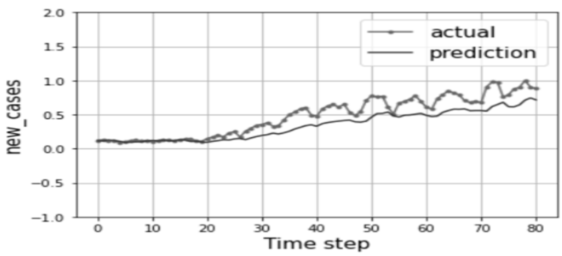

Figure 7. New Cases

6. Conclusion

CoVID-19 is a dramatically spreading disease around world, so it requires building a prediction model based on global health data. This work presented a hybrid model of LSTM and GRU algorithms built for the purpose of predicting the speed of disease spread among people in Iraq to assist accordingly identifying ways and actions of reducing spread of this disease via social distancing, online communication, and taking appropriate treatment and necessary vaccinations.

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Long Short-Term Memory and Discrete Wavelet Transform based Univariate Stock Market Prediction Model

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ABSTRACT

Analyzing financial situations in the current scenario is difficult, as it requires understanding the quality and value of investments. This study predicted the movement of stock prices in the Saudi Arabian stock market (Tadawul) over a one-week period using a proposed integrated model of Long Short-Term Memory (LSTM), which combines LSTM, Discrete Wavelet Transform (DWT), and Autoregressive Integrated Moving Average (ARIMA). Historical closing prices of a group of four companies listed on Tadawul were used as input for the proposed LSTM model, which consists of memory units capable of storing long time periods. Once the LSTM model predicted the closing values of stocks in Tadawul, they were further analyzed using the ARIMA model. The prediction accuracy of the proposed LSTM model and the traditional ARIMA model were 97.54% and 96.29% respectively. Therefore, the proposed integrated model of LSTM is considered a useful tool for predicting stock market values. The results emphasize the significance of Deep Learning (DL) and leveraging multiple information sources in predicting stock prices.

Keywords: Long Short-Term Memory, deep learning, prediction, Univariate, Discrete Wavelet Transform, stock market, Time series

1. Introduction

Forecasting, the process of predicting the future based on past and present data, has long been of interest in stock price prediction. However, due to the complex and constantly changing nature of the financial environment, accurately making these predictions is challenging[1]. Predicting stock market trends and prices is crucial in the investment and financial sectors, as it helps traders' profit from their trades. Various techniques, such as statistical and technical analysis, can be employed to forecast market prices [2].

The movement of stock prices is difficult to predict due to various unpredictable factors and noises. Factors like changes in sentiment, national economy, product value, political factors, and weather can influence stock prices on a daily basis [3]. Numerous researchers have studied stock price movements to understand the key factors that significantly impact stock prices [4]. Hence, this study aims to develop a hybrid model called the discrete long short-term memory (LSTM) model by combining a conventional LSTM artificial neural network (ANN) and a conventional discrete wavelet transform (DWT) ANN. The goal is to use this model to predict the prices of specific stocks on the Saudi Stock Exchange (TADAWUL) for a next one-week period.

Consumer sentiment plays a crucial role in influencing stock market price movements. Future research should explore the impact of financial events and the attitudes of stock buyers towards goods and services[5].This study compares the performance of the proposed LSTM model with conventional methods like the autoregressive integrated moving average (ARIMA) model. Various modeling techniques were evaluated, and the best model was selected after considering different model configurations.

This introduction examines the application of two prominent time series forecasting techniques: Long Short-Term Memory (LSTM) networks and Autoregressive Integrated Moving Average (ARIMA) models in predicting stock market behavior. To enhance prediction accuracy, we employed the DWT process, which uses unsupervised techniques to eliminate data noise. The data underwent DWT processing before being inputted into LSTM and subsequently ARIMA. LSTM, a recurrent neural network, excels at capturing long-term dependencies in sequential data, making it suitable for modeling the dynamic and non-linear nature of stock prices. On the other hand, ARIMA, a classical statistical model, leverages autoregression, differencing, and moving average components to analyze historical stock price trends. The integration of LSTM and ARIMA provides a comprehensive approach to forecasting stock market behavior, recognizing the importance of adaptability in response to ever-changing market dynamics.

This research is organized according to the following sections: After the introduction comes the second section, which is the covers previous studies on stock price prediction, while the third section introduces and explains the proposed methodology and its characteristics. The fourth section presents and discusses the experiments of this study, and the fifth section is the discussion and results, and then the last section, which is the conclusions and future work.

2. Literature review

It is essential to review extant studies prior to conducting research. In this study, Dou Wei (2019) compared and analyzed different methods for predicting neural networks. Ultimately, the study selected the LSTM neural network, which was optimized by the MBGD algorithm, to predict stock prices. The focus of the study was to assess the feasibility and applicability of this method. The study concluded that historical information is crucial for investors when making investment decisions. While previous studies mainly relied on opening and closing prices, this study found that absolute highs and lows can provide additional insights into future price behavior. To further investigate, the study selected three representative stock indicators in the Chinese stock market. The main data collected included the opening price, closing price, low price, high price, date, and daily trading volume. The results indicate that the LSTM neural network model, with the inclusion of the attention layer, can predict stock prices despite some limitations, such as time delay in forecasting. The model utilizes time sequence analysis of historical information and the selective memory function of the LSTM network to uncover internal rules and ultimately predict stock price trends[6].

Diqi, & el. (2022) This study demonstrates the effectiveness of using a generative adversarial network (GAN) for accurately predicting stock prices. We discuss the process of collecting and preprocessing the dataset, extracting features, evaluating the model, and implementing the GAN method for stock price forecasting. The GAN model consists of a generator and discriminator trained using adversarial learning techniques. Our model includes date, opening price, highest price, lowest price, closing price, and trading volume as training features. The experimental results show high accuracy and low error rates, indicating significant potential for precise and dynamic stock price predictions. Our proposed model achieves satisfactory results with an R2 score of 0.811166 for real expectations and 0.674971 for artificial expectations. The MAE function generates real expectations of 0.020665 and artificial expectations of 0.042406. The MRLE values are 0.001087 for real expectations and 0.002479 for artificial expectations[7].

The researcher Muhammad Ali (2022) proposed a mixed method that combines a new version of Empirical Mode Decomposition (EMD) signal analysis with Long Short-Term Memory (LSTM) network, which is a well-known technique for deep learning. We evaluate the accuracy of our proposed method using the KSE-100 index for the Pakistan Stock Exchange. Instead of the traditional Triple EMD technique, we use a new version called Akima-EMD to analyze the oscillatory data of stocks into multiple components known as Intrinsic Mode Functions (IMFs) and one residue. We then use the closely related sub-components to build the LSTM neural network. We compare the performance of our mixed model with the LSTM model, as well as other models such as Support Vector Machine (SVM), Random Forest, and Decision Tree. We use three statistical measures, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), to compare these techniques. Our experimental results show that the proposed Akima-EMD-LSTM mixed model outperforms all other models in this study, making it an effective model for predicting non-stationary and nonlinear financial time series data [8].

According to Patil et al. (2023), this research presents the Deep Recurrent Rider LSTM strategy as an effective method for accurately detecting stock market values. It combines two classifiers: Rider Deep LSTM and Deep RNN. Rider Deep LSTM combines the Rider concept with Deep LSTM, while Deep RNN is trained using the Shuffled Crow Search Optimization (SCSO) technique. SCSO is a combination of the Shuffled

Shepherd Optimization (SSO) algorithm and the Crow Search Algorithm (CSA). The expected output is determined based on error conditions. The proposed Deep Recurrent Rider LSTM achieves MSE and RMSE values of 0.018 and 0.132 respectively, indicating higher performance and accuracy. Overall, the proposed classification model enhances the accuracy of stock market prediction[9].

According to the study conducted by Bhupinder et al. (2023), this study aims to predict and estimate real-time stock assets in financial markets without relying on external brokers. We focus on broadcasting-based trading and utilize various performance factors and data metrics. Accurate sample data from the Y-finance sector is collected through API-based data chains. We employ reliable machine learning algorithms to classify and predict complexities. However, stock volatility and uncertainty can introduce noise and weaken decision-making. Previous studies used fewer performance metrics. In this study, we combine Dickey-Fuller test scenarios with volatility prediction and a short-term memory algorithm. This algorithm is implemented in a recurrent neural network to forecast closing prices of large companies in the stock market. To analyze forecast accuracy, we integrate LSTM methods with ARIMA and evaluate metrics such as root mean square error, mean square error, mean absolute percentage error, mean deviation, and mean absolute error. We design experimental scenarios to minimize hardware resource usage and conduct a test case simulation[10].

Using ARIMA and XGBoost sought to forecast Saudi Telecom Company stock price trends based on its historic prices by Almaafi et al. (2023), this study evaluates and compares the effectiveness of ARIMA and XGBoost models in predicting the weekly closing prices of Saudi Telecom Company stocks. Our results show that XGBoost outperforms ARIMA in all evaluation metrics, highlighting the effectiveness of machine learning techniques in stock price prediction. The study also sheds light on the limitations of traditional statistical models in forecasting stock price volatility and emphasizes the potential of machine learning techniques in discovering hidden patterns and trends in the data. Our research provides a comprehensive overview of the suitability of different forecasting models for predicting stock prices and emphasizes the need for further exploration of machine learning techniques in finance[11].

Meanwhile, another study used LSTM networks as a cutting-edge method of learning the arrangements. Although these networks were mostly utilized with financed-based time series data, they are inherently relevant. For predicting the directional trend of the unseen data of the Standard and Poor's 500 (S&P 500) index's equities, this present study used LSTM-based networks. Additionally, factors that affect profitability are addressed, revealing details about how complex artificial neural networks function. Stock trading shows high volatility and exhibits a short-term reversal trend [12].

Jarrah and Derbali (2023) introduced a novel approach to predicting stock market indices in the Kingdom of Saudi Arabia (KSA). The study utilized opening, lowest, highest, and closing prices as variables to assist investors in making informed decisions. To eliminate noise from the input data obtained from the Saudi Stock Exchange (Tadawul), exponential smoothing (ES) was employed. The time series forecasting task was addressed using a sliding-window method with five steps. The prediction of stock market prices was carried out using a multivariate long short-term memory (LSTM) deep-learning (DL) algorithm. The proposed multivariate LSTM-DL model demonstrated its effectiveness in forecasting stock market prices, achieving prediction rates of 97.49% and 92.19% for the univariate model. These results highlight the accuracy of DL and the utilization of multiple information sources in predicting stock market trends [13]. Table 1 below summarizes the Literature review. The main contributions of this article are as follows:

- Applies DWT to Noise Reduction, using it to remove noise from the dataset and extract relevant features for predicting stock prices. This improves the quality of input for LSTM and ARIMA models.
- The LSTM and ARIMA models demonstrate adaptability by learning from historical data and adjusting to changing market conditions. This makes them suitable for predicting stock prices influenced by a mix of short-term and long-term factors.
- The research utilizes the lag feature also known as the delayed feature, for data analysis and prediction, primarily in time series analysis.

Authors	Year	Title	Algorithm	Dataset	Accuracy
Dou Wei[6]	2019	Prediction of Stock Price Based on LSTM Neural Network.	LSTM, Mini-Batch Gradient Descent (MBGD)	Chinese stock market	Classification
Diqi, & el [7].	2022	StockGAN: robust stock price prediction using GAN algorithm	Generative Adversarial Network (GAN)	Yahoo finance	R2 = 0.811166. MAE = 0.020665 MRLE = 0.001087

Muhammad Ali & el.[8]	2022	Prediction of complex stock market data using an improved hybrid emd-lstm model	LSTM & Empirical Mode Decomposition (EMD)	Pakistan Stock Exchange	RMSE = 317.504 MAE = 246.675 MAPE = 0.711
Patil et al.[9]	2023	Wrapper-Based Feature Selection and Optimization-Enabled Hybrid Deep Learning Framework for Stock Market Prediction	RNN, LSTM, Shuffled Crow Search Optimization (SCSO) technique	Yahoo finance	MSE = 0.018 RMSE = 0.132
Bhupinder et al.[10]	2023	Auto-Regressive Integrated Moving Average Threshold Influence Techniques for Stock Data Analysis	LSTM, ARIMA	Yahoo finance	LSTM RMSE = 2.50113 ARIMA RMSE = 0.0238892
Almaafi et al. [11]	Almaafi et al. (2023	Stock price prediction using ARIMA versus XGBoost models: the case of the largest telecommunication company in the Middle East	ARIMA, XGBoost	Saudi Telecom Company	Classification
Fischer & Krauss [12]	2018	Deep learning with long short-term memory networks for financial market predictions	LSTM, random forest	S&P 500	Classification
Jarrah & Derbali [13]	2023	Predicting Saudi Stock Market Index by Using Multivariate Time Series Based on Deep Learning	LSTM, Exponential smoothing (ES)	stock market of the Kingdom of Saudi Arabia (Telecommunication)	RMSE multivariate = 0.404 RMSE univariate = 0.552

Table 1. Literature review

3. Proposed Methodology

This research introduces the LSTM, ARIMA and DWT because the field of time series analysis has witnessed significant progress in the field of deep learning techniques. Among these techniques, Long Short-Term Memory (LSTM) networks have emerged as a powerful tool for modeling and predicting sequential data, especially univariate sequential data. Time series, which represent sequentially ordered data points, are abundant in various fields, including finance, economics, medicine, and environmental sciences. Researchers and specialists understand time series contain noise, and to obtain accurate forecasts, it is necessary to remove the noise. Therefore, the Discrete Wavelet Transform (DWT) is integrated as a first step to denoise the data before entering the second phase, which is the LSTM. The attached Figure. 1 below illustrates the stages of the proposed model. The effectiveness of an LSTM model relies on the quality of the data, the architecture and hyperparameter choices, and domain expertise. To obtain accurate and meaningful results, it is essential to experiment, iterate, and possess a profound understanding of the underlying principles.

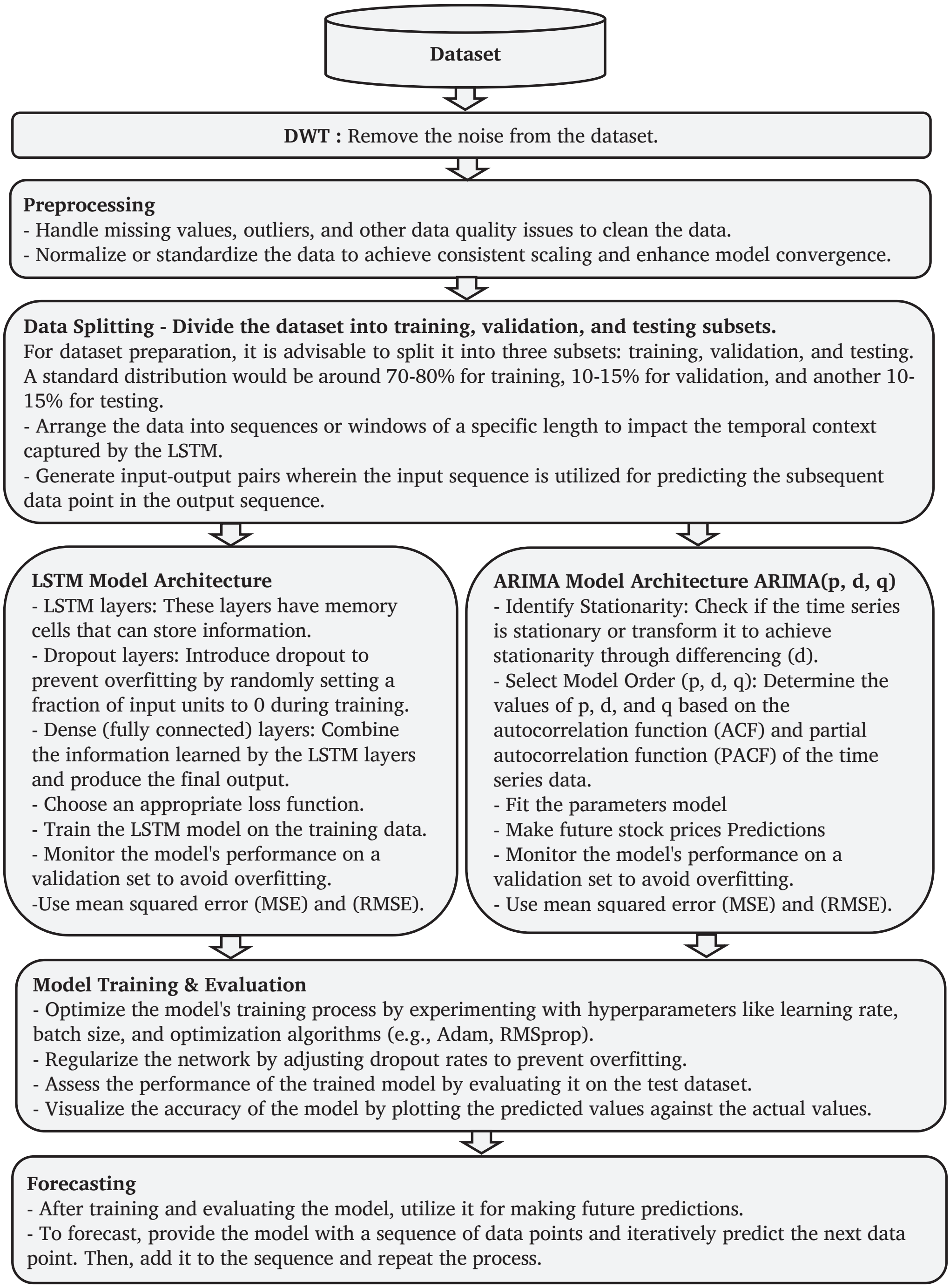

Figure 1. Proposed Methodology

3.1. Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is an analytical technique used for signal and multi-dimensional data analysis. DWT works by dividing the signal into wavelet components across a specified set of basic waves, allowing analysts to understand signal details at different levels of detail and frequencies. Regarding the use of DWT in eliminating input data noise, it can definitely play a role in improving signal quality and getting rid of noise. The basic idea here is to utilize DWT's unique ability to represent the signal at multiple levels of detail, enabling the separation of important and useful signal components from those affected by noise. The general steps for using DWT to eliminate input data noise include [14]:

- DWT Transformation: Applying DWT to the input signal to transform it into a set of wavelet components at different levels of details and frequencies.
- Noise Estimation: Estimating the type and level of noise in the wavelet components at different levels.
- Filtering Noise-Affected Components: By separating the noise-affected components and either ignoring or appropriately modifying them.
- Inverse DWT Transformation: After filtering the noise-affected components, an inverse transformation should be performed to return to the time domain.

The use of DWT in eliminating data noise relies on a good understanding of the signal and the present noise, as well as identifying the appropriate levels of detail that contain vital information and those that carry noise. If these steps are executed correctly, DWT an contribute to improving data and signal quality by eliminating annoying noise[15]. The Figure 2 shows the benefits of using the DWT, where the noise in the input data is eliminated before entering it into the proposed model.

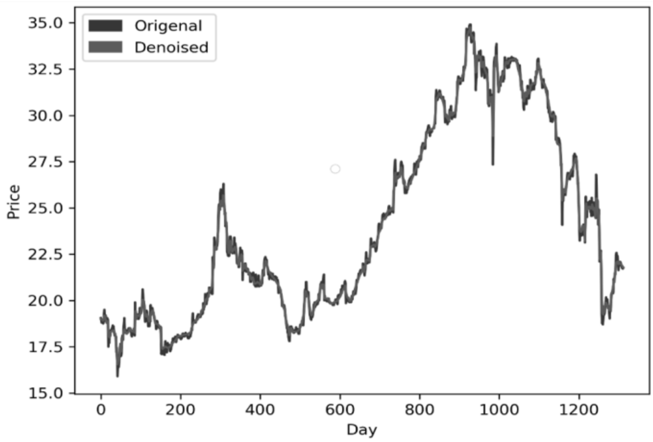

Figure 2. Output dataset after removed the noise by DWT

3.2. Long Short-Term Memory (LSTM)

An LSTM, known as Long Short-Term Memory, is a recurrent neural network (RNN) architecture that effectively captures long-range dependencies in sequences. It tackles common problems faced by traditional RNNs, such as the vanishing gradient problem. This is achieved by incorporating specialized gates that regulate the information flow within the network. The three main gates in LSTM networks are the forget gate, the input gate, and the output gate. Each gate has a distinct role in managing the flow of information. Figure 3 below explain that gates.

The forget gate helps the LSTM decide what information to discard from the cell state (the memory of the network) from the previous time step. It takes the previous hidden state (h_[t-]) and the current input (x_t) as inputs and produces a value between 0 and 1 for each element in the cell state. This value represents how much of the information from the previous cell state should be forgotten and how much should be retained. [Ref] Mathematically, it is calculated as:

$$f_t = \sigma\left(W_f[h_t - 1, X_t] + b_f\right) \tag{1}$$

Here, W_f and b_f are the weights and bias associated with the forget gate, and σ is the sigmoid activation function.

The input gate helps the LSTM decide what new information to update in the cell state from the current input. It also consists of two parts: the first part calculates a candidate cell state update (C̃_t), and the second part determines which portions of this candidate update to add to the cell state. The input gate takes the previous hidden state (h_[t-1]) and the current input (x_t) as inputs. Mathematically, the calculations are as follows:

$$i_t = \sigma(W_i[h_t - 1, X_t]) + b_i \tag{2}$$

$$C_t = \tanh(W_c\,[h_t - 1, X_t] + b_c) \tag{3}$$

The output of the input gate is i_t, represents how much of the candidate update to add to the cell state. where, *tanh* is the function that activates the state [13].

Cell State Update: The actual update to the cell state (C_t) is a combination of forgetting some previous information and adding new information. This is done by multiplying the previous cell state by the forget gate output and adding the candidate update scaled by the input gate output:

$$C\_t = f_t * C\_(t\text{-}1) + i_t * C_t \tag{4}$$

Output Gate: The output gate determines the new hidden state for the current time step. It takes the previous hidden state (h_(t-1)), the current input (x_t), and the updated cell state (C_t) as inputs. It produces a new hidden state for this time step (h_t). Mathematically, the calculations are as follows:

$$O_t = \sigma\,(W_o\,[h_t - 1, X_t] + b_o) \tag{5}$$

$$h_t = O_t * \tanh(C_t) \tag{6}$$

The output gate regulates the extent to which the cell state is revealed as the hidden state. In essence, LSTM gates govern information flow in the network by deciding what to forget, what new information to incorporate, and how to update the hidden state [16]. This architecture empowers LSTMs to effectively manage long-range dependencies and capture contextual information in sequential data.[17]. Figure 2 below illustrates the gates.

The term "sliding window size" in LSTM networks refers to how the LSTM processes sequential data. Sequential data includes time series and natural language sentences, where the order of elements matters. The sliding window size determines the number of time steps the LSTM considers at a time. It acts like a moving window that slides through the sequence. For example, if the sequence has timestamps from t=1 to t=10 and a sliding window size of 3, the LSTM will initially consider inputs from t=1, t=2, and t=3. Then it would slide the window to consider t=2, t=3, and t=4, and so on.

When processing data using a sliding window, the LSTM considers the input data within that window to produce an output, such as a prediction or classification. This approach allows the LSTM to capture patterns and dependencies spanning a specific number of time steps.

The choice of sliding window size has trade-offs. A larger window size can capture longer-term dependencies but increases model complexity and computational intensity. A smaller window size captures short-term dependencies well but may miss longer-term patterns. To ensure important transitions between adjacent windows are not missed, overlapping sliding windows are commonly used. For instance, with a window size of 3 and overlapping by 1, the LSTM would process t=1, t=2, t=3, then move the window to t=2, t=3, t=4, and so on. In practice, the choice of sliding window size depends on the data characteristics and the specific problem being solved. It is often a hyperparameter that needs to be tuned along with other LSTM architecture parameters to achieve optimal performance for the task at hand.

The LSTM (Long Short-Term Memory) neural network algorithm has been used in stock price prediction for several reasons. Here are some reasons that make LSTM suitable for this task:

- Ability to handle time series:

Stock prices are time series, where today's price depends on the previous days' prices. LSTMs are designed to handle sequential data and interact with events over time, making them suitable for analyzing and predicting stock prices.

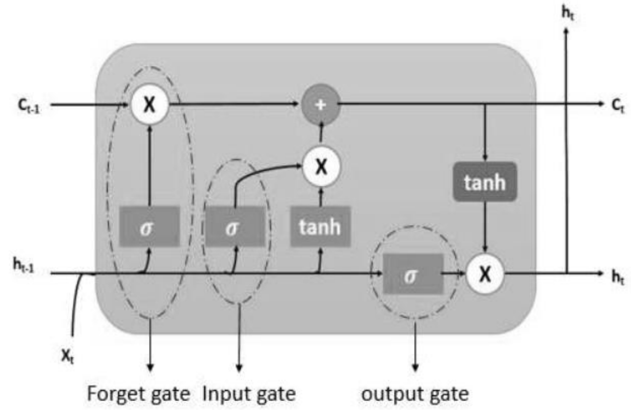

Figure 3. LSTM Gates [18]

- Providing temporal representation of information:

LSTMs retain internal memory that allows them to store and retrieve information over time. This helps in dealing with events that may be significant in the future and their impact on stock prices.

- Handling non-linearity and complex patterns:

The stock market is characterized by complex and volatile data. LSTMs are good at handling non-linear patterns and complexity in data, as they can understand and analyze the non-linear relationships between factors influencing stock prices.

- Ability to learn from the past:

LSTMs can learn complex relationships and patterns in data, thanks to their ability to use short-term memory to store and utilize important information for prediction.

- Dealing with the vanishing gradient problem:

LSTMs have a mechanism called "gates" that helps overcome the vanishing gradient problem, which is a problem faced by traditional neural networks when trying to train models on long time sequences.

Despite these benefits, the use of LSTM should be done carefully, often requiring consideration of other factors such as data quality, data volume, and indicators used to ensure achieving the best performance in stock price prediction task.[13]

3.3. Autoregressive Integrated Moving Average (ARIMA)

A linear model called ARIMA combines autoregressive (AR), moving average (MA), and differencing (I) components. It uses three parameters, p, d, and q, to model seasonality, trend, and noise in a time series.

The parameter p represents the autoregressive aspect of the model, incorporating past values. For example, if it rained heavily in the past few days, we could forecast that it is likely to rain tomorrow as well. The parameter d is associated with the integrated part of the model, determining the amount of differencing applied to the time series. For instance, if the daily amounts of rain have been similar over the past few days, we can forecast that tomorrow's rainfall will be similar to todays. The parameter q is related to the moving average part of the model.

If our model includes a seasonal component (explained later), we use a seasonal ARIMA model (SARIMA) with additional parameters: P, D, and Q. These parameters have the same associations as p, d, and q but correspond to the seasonal aspects of the model. Our methods only consider data from a univariate time series, focusing solely on the relationship between the y-axis value and the x-axis time points. We do not take into account external factors that may influence the time series. [6], [19]

4. Experiments Authors

The present study was conducted using the historical price data of four high volume stocks; namely, Saudi Arabian Mining Co, Yanbu Cement Co., Sabic, Saudi Indian and TSLA as a benchmark; over a period of 1132, days; specifically, from 1 January 2019 to 23 July 2023. They were obtained from the website https://www.investing.com/equities/ on 25/7/2023. Only the closing prices of the aforementioned stocks were used to univariately forecast their closing prices for the subsequent seven days. The company's data was used, and the general market index was not used because the aim of the research is to assist investors in identifying the appropriate company for investment. The general index provides an overall view of market behavior and cannot determine a specific company. The dataset was divided into two groups, the first for training with a total of 906 records, which is 80%, and the second for testing with a total of 226 records, which is 20%. Table 2. provides a summary of the statistics of the input data:

	Saudi Arabian Mining	**Saudi Basic Industries**	**Saudi Riyal Indian**	**Yanbu Cement**	**TSLA**
count	1132	1132	1132	1132	1132
mean	25.491422	103.337102	20.040194	36.194373	163.507069
std	13.164116	16.615524	1.077733	5.508642	110.823442
min	9.330000	62.000000	18.230000	22.200000	11.930000
25%	14.192500	89.875000	19.180000	32.737500	37.510000
50%	18.865000	100.200000	19.850000	36.800000	186.790000
75%	40.670000	120.650000	20.690000	40.050000	246.690000
max	56.930000	139.000000	22.100000	48.450000	409.970000

Table 2. The statistics of the input data

In this research, the lag feature is used in data analysis and prediction, particularly in time series analysis. Time series analysis involves analyzing data that changes over time, such as price series, monthly revenues, and industrial production. Lag features involve using previous values of a variable as inputs in a predictive model to forecast future values of the same variable. For example, in analyzing a time series of commodity prices, lag features can be created based on past prices. By incorporating these lag features, the model can better predict future values since current price changes can influence future values. Similarly, when analyzing sales data for a specific product, a lag feature can be created using the sales from the previous month. Including this lag feature as an input in the prediction model improves the accuracy of future forecasts. In summary, lag features introduce a temporal aspect to analysis and prediction models, allowing them to capture relationships and transitions in data over time. This incorporation enhances their ability to predict future events.

4.1. Analyzing Autocorrelation and Partial Autocorrelation

Autocorrelation (ACF) and partial autocorrelation (PACF) are vital tools for understanding the underlying patterns in our time series data. ACF measures the correlation between a time series and its lagged version, while PACF measures the exact correlation while accounting for the effect of other lags. By examining the ACF and PACF plots, we can identify the appropriate lags for our forecasting models.

4.2. Forecasting process

The first LSTM model parameter that requires tuning is the number of training cycles. The next parameter is the size of the batch, which determines the frequency of updating the weights of the network. The third factor that affects the system's learning capacity is the number of neurons. The Adam-optimized approach was employed as it is based on the stochastic gradient descent optimization algorithm, which is popularly used in DL. The ability of a system to learn an issue structure often correlates with the number of neurons present, even when training time is lengthened. However, a higher learning capability causes the issue of training data overfitting. Table 3 includes a list of the test parameters as well as average values for the prediction accuracy, including the mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE) of all the cases.

Experiment	Epochs	Batch Size	Neurons	MAE	MSE	RMSE
1	120	8	4	0.58	0.34	0.346
2	150	4	4	0.43	0.49	0.518
3	170	4	5	1.53	4.48	2.621
4	190	4	5	0.37	0.28	0.56
5	210	4	6	1.46	4.28	2.586

Table 3. Experiment Specifics Experiments

The findings presented in the table showed that Test 4 yields the most optimal results. Table 3 contains the information related to the sample that was selected and consists of four companies listed on the TADAWUL Saudi stock market.

The LSTM and ARIMA models were used to process all the data. The dataset of the TSLA was further divided into testing and training datasets. The training dataset comprised the initial 1132 entries and was used to create the models. The other entries made up the testing dataset and were used to verify the model by forecasting the results.

The time step of every dataset increased by one. The model was used to forecast the time steps. The anticipated values of the testing set were entered in the model to estimate the subsequent step. This scenario is analogous to a real-world scenario in which the most recent stock market information is retrievable on a daily basis and used to forecast the following day's prices. The testing dataset-based predictions were compiled, and their error rates were computed to determine the forecasting capability of the model, which was then tuned using the MAE, MSE, and RMSE metrics, where the higher errors were adjusted to enable more optimized results that were consistent with the actual data.

4.3. Model Evaluation

When evaluating a time series machine learning model, it is crucial to conduct error analysis. This involves calculating the discrepancy between the predicted and actual values for each data point, allowing you to assess the model's accuracy. There are various methods for error analysis, including the choice of evaluation metrics such as mean squared error (MSE), mean absolute error (MAE), or root mean squared error (RMSE). The use of mean squared error is suitable for models that can adapt to sudden changes in the data distribution. On the other hand, mean absolute error is more appropriate for models that do not swiftly react to changes in the data distribution.

5. Discussion and results

To validate the model, the researchers employed Python 3.8 which could be run using the Windows 10 operating system (OS). Many Python libraries were employed in this present study, including the fundamental object in Numpy which is a homogeneous multidimensional array. It could be seen as the element table, which normally contains numbers of the same value. Python's built-in Pandas module offers versatile, quick, and expressive process-es that are designed to produce "labelled" and "relational" data that can be interpreted easily. A library called Sklearnit offers simple and effective data assessment.

Also, Theano, TensorFlow, or the MS Cognitive Toolkit can all be used for executing the Keras library. This package focuses on modularity, extensibility, and user-friendliness and helps in rapid testing using DNNs. Finally, the NumPy mathematical extension is used in addition to the Matplotlibit module, a Python plotting tool. The data presented in Figure 4, Figure 5, Figure 6, and Figure 7. Table 4 offers information on the actual and forecasted stock prices as well as data on the accuracy of the forecasts and indicators of errors, such as MSE, MAE, and RMSE appears in Table 5 and Figure 8. Furthermore, presents the brief of the accuracy generated by applying the recommended LSTM framework. The obtained results show a very small error rate, indicating the quality of the results and the ability of the LSTM algorithm to predict stock prices.

Company		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Saudi Arabian Mining Co.	Actual	43.40	43.80	44.25	44.40	44.50	44.30	44.30
	LSTM	43.47	43.81	44.18	44.31	44.40	44.23	44.23
	ARIMA	43.21	43.53	43.92	44.30	44.29	44.01	44.21
Yanbu Cement Co.	Actual	40.00	40.50	40.95	40.60	40.60	40.45	39.45
	LSTM	40.19	40.68	41.09	40.77	40.77	40.623	39.65
	ARIMA	39.9,	40.2	40.0,	39.8,	39.9,	40.0,	40.2
Sabic	Actual	84.4	85.5	86.1	87.0	88.2	88.4	88.5
	LSTM	84.12	85.30	85.94	86.91	88.19	88.40	88.51
	ARIMA	85.0	85.2	85.8	86.2	87.5	87.2	88.9
Saudi Indian	Actual	21.84	21.87	21.86	21.86	21.87	21.87	21.85
	LSTM	21.82	21.84	21.83	21.83	21.84	21.85	21.83
	ARIMA	21.90	21.81	21.94	21.99	21.92	21.94	21.91

Table 4. Forecasts for The Subsequent Seven Days

Company		MAE	MSE	RMSE
Saudi Arabian Mining Co.	LSTM	0.0693	0.0057	0.0757
	ARIMA	0.154	0.0914	0.101
Yanbu Cement Co.	LSTM	0.1724	0.0301	0.1732
	ARIMA	0.413	0.0984	0.289
Sabic	LSTM	0.1109	0.0229	0.1514
	ARIMA	0.214	0.131	0.214
Saudi Indian	LSTM	0.0310	0.0009	0.0310
	ARIMA	0.195	0.0451	0.214

Table 5. Forecasts for The Accuracy

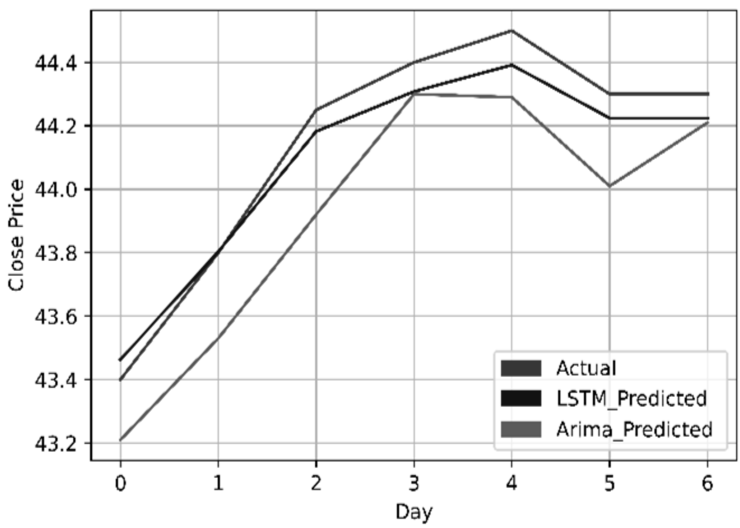

Figure 4. Forecasts for the Saudi Mining Co.

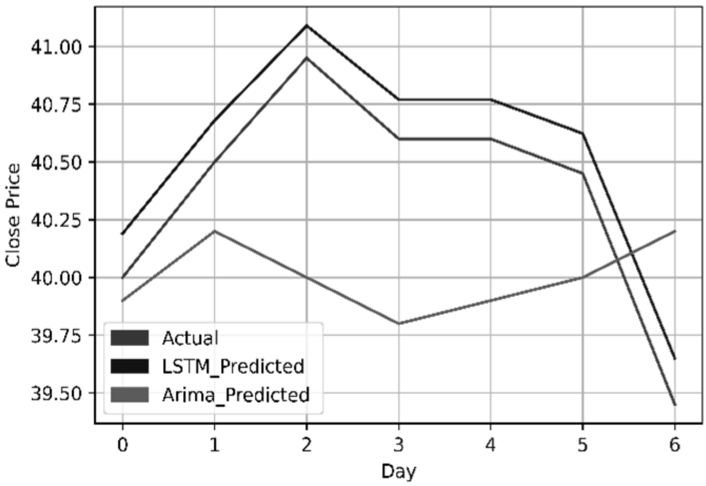

Figure 5. Forecasts for the Yanbu Cement Co.

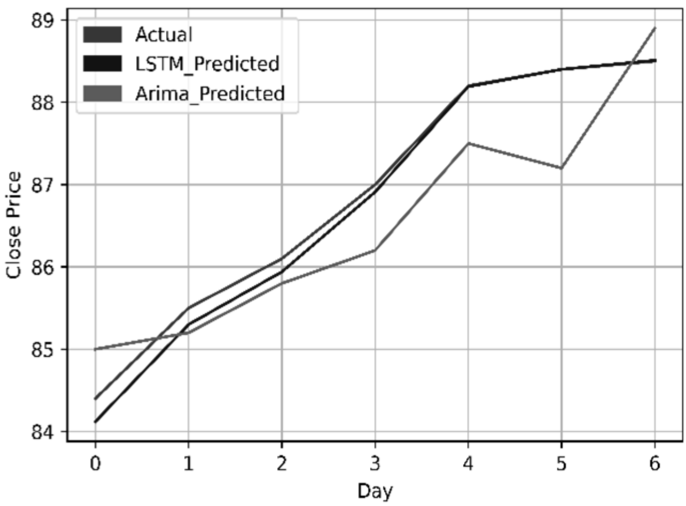

Figure 6. Forecasts for Sabic

The second step involved testing the TSLA Index using the ARIMA and LSTM models. Data related to the model results over the one-week period is presented in Figure 7 and Table 6.

Index		**Day 1**	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**
TSLA	Actual	23.1870	23.0596	22.6296	22.4180	22.3859	21.2397	20.0817
	LSTM	23.000	22.5700	22.3600	22.3300	21.1800	20.0200	20.6700
	ARIMA	26.063	25.074	25.424	25.095	24.477	23.126	23.780

Table 6. Forecast One Week (TSLA Index)

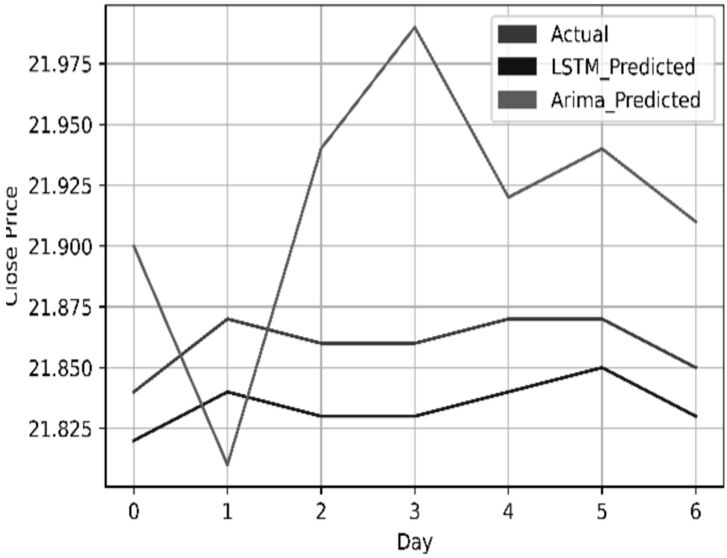

Figure 7. Forecasts for Saudi Indian

Comparison of the proposed LSTM and ARIMA models' forecasts vs. actual performance from the TSLA index over a one-week period. The accuracy of the forecasts and indicators of errors, such as MSE, MAE, and RMSE appears in Table 7 And Figure 8.

Index		MAE	MSE	RMSE
TSLA	LSTM	0.578	0.520	0.721
.	ARIMA	0.989	0.951	1.041

Table 7. Forecast for The Accuracy (TSLA Index)

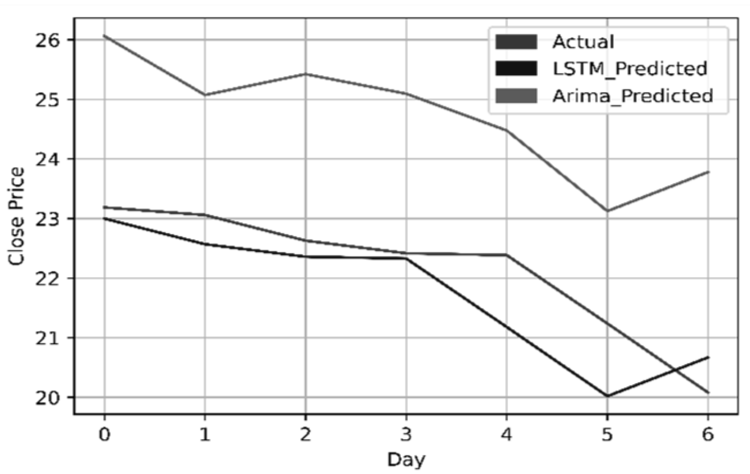

Figure 8. TSLA index

5. Conclusions and future work

The current study investigated strategies for predicting stock prices in the near future. The study applied the ARIMA algorithm and the LSTM algorithm after using DWT to eliminate noise from the input data. These predictions aid investors in making informed decisions regarding stock market investments. Below, we summarize our findings for each algorithm:

ARIMA is a powerful model that yielded the best results for stock data. However, it requires precise hyperparameter tuning and a good understanding of the data.

Recurrent Neural Networks (RNNs) based on LSTM are particularly effective for learning from sequential data, including time series. These models shine when working with large datasets and can uncover complex patterns. Unlike ARIMA, they do not rely on specific assumptions about the data, such as time series stationarity or the presence of a timestamp. However, interpreting the behavior of LSTM-based RNNs can be challenging. Additionally, achieving good results necessitates precise hyperparameter tuning.

Future studies on this subject should consider various factors to enhance prediction accuracy. For instance, the impact of events and annual seasons like Umrah, Hajj, and Ramadan on stock price movement accuracy should be examined using trading data.

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Original Scientific Paper

Blended Learning in the Spotlight of Educational Management - A Scientometric Analysis

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ABSTRACT

The mass adoption of ICT for online delivery of education due to the COVID-19 pandemic has brought many opportunities but also challenges for the education sector. In this paper, we conducted a scientometric analysis to provide insights into research trends and present bibliometric indicators of 5810 publications on blended learning to contribute to the knowledge base on the use of ICT in education management, during and after the COVID-19 pandemic, from 2020 to 2023. The number of citations and publications increased rapidly. Content analysis of the publications and keyword analysis revealed important and emerging topics such as the challenges and experiences of students, teachers and institutions with blended learning, especially in higher education, from implementation and use to digital literacy, attitudes, performance, self-regulation and learning outcomes. The main journals focused on the use of technology in education and health education. Blended learning has likely moved beyond the pandemic and has become an integral part of management in educational organizations.

Keywords: blended learning, education, bibliometric analysis, educational management, online learning, literature review

1. Introduction

During the COVID-19 pandemic, and especially during the lockdown aimed at reducing physical contact, there was a global urgency to provide solutions for fully online education in education systems around the world. The education sector was among the best prepared sectors, as the accelerated adoption of ICT technologies in classrooms began more than a decade earlier. Therefore, some educational institutions that were already well-equipped and had previously used some forms of online education began systematically using ICT technology, while others took the opportunity to better equip the institution with technologies they did not previously have, with the common goal of making online teaching and learning as available and high quality as possible [1]. While the technological solutions were largely in place, so was the basic knowledge of online and other forms of technology-enhanced teaching and learning. Due to the proliferation of educational enhancements through ICT in recent years, especially during the COVID-19 pandemic, many new expressions and terminologies have emerged, such as “blended learning”, “hybrid learning”, “distance learning”, “e-learning” and many others, causing confusion in choosing the correct expression and highlighting the need for clarification of terminology. The need to clarify some of these expressions and terms according to their meaning has been recognised by several authors [2], [3].

The impact of the COVID-19 pandemic was also reflected in the production of scientific publications in the field of education that focus on the introduction of new technologies in the classroom. While the period 2015 to 2020 has seen a decrease in the number of publications on e-learning as a new trend in teaching [1], the number of publications on the topic of newer forms of merging online and face-to-face teaching, such as hybrid teaching and blended learning, has increased, especially in the last three years after the COVID-19 pandemic. Whereas 20 years ago scholarly interest focused on the impact of online education on learners and the influence of asynchronous learning, scholarly interest has now shifted to learner satisfaction and informal learning [4].

In recent years, bibliometric analysis of publications has proven useful in summarising the knowledge base in emerging and rapidly growing research areas. For example, publications on bibliometric analysis have increased in the field of education focusing on teaching methodology as well as online teaching and learning, especially in the context of new technologies in education and Education 4.0 [5], [6]. The bibliometric analysis has shown that the active use of newer forms of teaching in an online environment such as blended learning and hybrid learning [7], [8] and the development of topics such as digital health education, blended learning environment, observed learning and others are increasing rapidly, but the collaboration between authors and universities is still very low [1]. However, research on the impact of COVID-19 period on online teaching and learning is not yet fully investigated.

In this paper, we make several contributions. First, we distinguish the differences between blended learning and hybrid learning as very similar but different concepts that are sometimes used as synonyms. Second, we analyse the rapidly developing research area of blended learning during and after the COVID-19 pandemic period and teaching to provide a knowledge base for the field. We identify the most productive journals, organisations, and countries, as well as the most important publications and the most relevant and emerging publication topics, using widely accepted qualitative and quantitative bibliometric indicators through a bibliometric analysis. Third, we enrich the bibliometric analysis with a content analysis of the most relevant publications during and after the period of the COVID-19 pandemic to highlight the main lessons learned from the rapid global adoption of ICT in education and its impact on education management.

The structure of the paper is as follows. In Section 1 we provide a literature review of previous research on blended learning and distinguish the terminology. In Section 2, we present the data and methodology. In Section 3, we present the results of several bibliometric analyses. We also present a content analysis of the most influential publications. In Section 4, we discuss the results, conclude, discuss limitations of our work and provide directions for further research.

2. Blending the Prior Research

During the COVID-19 pandemic, many educational institutions were faced with the rapid uptake of online teaching and learning tools and practises. To facilitate online teaching and learning, first, the technical infrastructure had to be supported. Second, each institution had to decide which approach to online teaching and learning was best for its institutional culture and student needs. Each institution decided on the most appropriate way to continue the teaching process unhindered; through different learning management system (LMS) platforms with different approaches such as hybrid learning, blended learning, synchronous type of online teaching versus asynchronous type of online teaching [9].

Both blended learning and hybrid learning were known and used in education before the pandemic, and the pandemic accelerated the adoption of these new learning models as a necessity to cope with the new situation [9], [10]. Very often the two pedagogical approaches of blended learning and hybrid learning are combined, and sometimes they are extended with other approaches such as flipped classroom, flexible learning, flipped learning and hyflex learning, which are known as variants of blended learning [7]. However, there is confusion regarding blended teaching and learning and hybrid teaching and learning stems from the fact that the terms are sometimes used interchangeably, referring to the same practices, while they are also used to refer to slightly different practices. In addition, the terms may be interpreted differently in different regions due to different educational traditions and are sometimes defined very similarly, so it can be very difficult to give a universal definition for each term [7]. The main difference, according to several authors, is that blended teaching and learning sometimes requires physical meetings between lecturers and learners, and the delivery method for certain topics is strictly prescribed by the curriculum, while hybrid teaching and learning leaves it up to the learners to decide whether to follow the lecture in person or online, with online teaching being as synchronized as teaching in real classrooms [11], [12].

Blended teaching and learning and hybrid teaching and learning can also be distinguished by the amount of time spent on in-person and online delivery of lectures. Although not a consensus, at least 50% of total course time in a blended learning model should be devoted to face-to-face teaching and learning [13], [8].

Both learning models enable flexible learning in collaboration between learners and teachers, except that hybrid learning can be much more tailored to the needs of learners and teachers, e.g., in terms of speed, time, and especially space [12]. Since there is confusion in the academic literature about the (di)similarities between blended and hybrid learning, we also consulted the most popular online dictionaries to capture a broader perspective on the terminology used: Oxford Learners Dictionaries, Cambridge Dictionary, Dictionary.com, and The Free Dictionary.

The definition of "blended learning" is found in all four dictionaries and emphasises, with some minor differences, the combination of traditional classroom learning with learning via the Internet or online. The Oxford Learners Dictionary and the Cambridge Dictionary do not include a definition of "hybrid learning". A definition of "hybrid learning" is found only on Dictionary.com, and that definition emphasises the combination of simultaneous classroom and online instruction, while The Free Dictionary automatically redirects the term "hybrid learning" to "blended learning". Although the terms "hybrid learning" and "blended learning" can be considered related in linguistics, the term "blended learning" is better known and more used. In addition, a review of the Web of Science Core Collection database (WoS CC) shows that most publications on hybrid teaching and learning come from the fields of engineering, computer science, and telecommunications, and only a small percentage of publications come from education and educational research fields. In contrast, most publications on blended learning come from the fields of education and educational research. Thus, it can be concluded that in the field of education the term "blended learning" is predominant, while in various technical fields the term "hybrid learning" is predominant.

Since we are interested in the field of education where the term "blended learning" is most commonly used, we will focus exclusively on "blended teaching and learning" in the remainder of this text. Furthermore, since the technology for online teaching and learning already exists due to the need to deliver education in the COVID-19 pandemic period, it is more plausible that some educational institutions will continue to use ICT to deliver some of the lectures online even in the post-pandemic time.

Even before the COVID-19 pandemic, emphasis was placed on blended learning because ICT has entered all aspects of life and its use can facilitate learning for rural or working populations, making learning more accessible. Research on blended learning addressed different methods of educational delivery, learners' experiences and preferences, and learners' learning outcomes and performance, which are particularly important when evaluating different methodological approaches in education. The main trends and themes of publications on blended teaching and learning have evolved since 2000, and the major themes have been instructional design (models, strategies, best practices, etc.), disposition (style, perceptions, preferences, etc.), exploration (benefits, trends, etc.), and learning outcomes (performance, satisfaction, engagement, etc.) [14]. Themes such as comparison to face-to-face classes, technology, and interaction were significantly less represented. Similar themes about blended learning with particular emphasis on instructional design were also highlighted in older publications, long before the integration of ICT into everyday life that we are experiencing today. The focus on instructional design research was highlighted as important, but there was a clear lack of theoretical underpinnings for online learning research, and the need for independent theory to further develop the field was emphasised [15].

In a systematic review, conducted before the mandatory uptake of online learning and teaching during COVID-19 pandemic, the biggest challenges of blended learning were incorporating flexibility, stimulating interaction and facilitating learning progression. Furthermore, the findings show that little attention is paid to instructional activities that promote an effective learning climate and that there is wide variation in how flexibility is incorporated into blended learning practices in terms of sequencing of activities and the relationship between online and face-to-face learning events [16]. The systematic review conducted by Rasheed and colleagues indicated that the online component of blended learning presents challenges for both educational institutions, teachers, and learners or students [17]. To deliver online teaching and learning, contemporary and technology of sufficient quality needs to be in place.

The main challenges for teachers were the reluctance to use and learn new technologies needed to facilitate online teaching and learning. The uptake of new technologies challenged teachers' technological literacy, ability to create high-quality video materials, as well as teachers' attitudes and beliefs about using technology in teaching. The main challenges for learners were the self-regulation and overall focus on technology rather than on learning. Understanding self-regulatory behaviours and relating them to a blended learning environment was the goal of Van Laer and Elen. Their findings showed that an educational institution's success in implementing self-regulatory features impacts not only learners who are good at self-regulation, but also those who regulate poorly [18]. Furthermore, when examining the preferences of a large group of students for combining online and face-to-face content, blended learning as a combination of online courses and face-to-face tutorials was rated highest, and students were found to enjoy the social aspect of learning [19]. In addition, student characteristics and attitudes toward computers, classmate characteristics, and course quality and flexibility have been shown to be related to creating and maintaining a positive user experience and attitude toward learning [20]. Factors that influence students' academic performance in blended and traditional learning environments have also been researched [21].

In considering the effects of blended learning on learner performance, the COVID-19 pandemic has provided a natural experiment from which more thorough and detailed studies are emerging. For example, the results of a study were recently presented in which students demonstrated that blended learning provided students with better grammatical knowledge and skills than online-only learning [22]. However, as a recent systematic review of systematic reviews on blended teaching and learning shows, currently blended teaching and learning is mainly studied in the context of higher education institutions, research mostly targets the perspective of students and learners, most research is conducted in developed countries, and the main barriers are the lack of equipment in educational institutions and the lack of ICT skills among teachers and students [23].

Although the need to adopt online learning approaches during the COVID-19 pandemic has given researchers the opportunity to evaluate the overall impact of using ICT for online teaching and learning, this area of research is still evolving, and blended teaching and learning is one of the focuses of educational management research.

In general, educational management is the process of planning, organizing, directing and controlling activities within an educational institution in order to effectively achieve its objectives. The primary goal of educational management is to ensure the smooth running of schools, colleges and universities, with a focus on improving the quality of education. The importance of educational management lies in its role as the backbone of an institution's success. Effective management ensures that —human, financial and material resources are optimally utilized to create a conducive learning environment. Since educational management plays a crucial role in promoting innovation and ensuring continuous improvement of teaching methods, modern practices such as blended learning and other similar ITC-supported innovations are actually part of educational management. Educational management should therefore also provide structured support in distance and blended learning environments, helping teachers to focus on their core tasks — teaching and mentoring — while responding to the diverse needs of students.

Educational leaders in blended learning environments need to manage change by building capacity in several key areas [24]. They should develop and implement plans to transform teaching into a personalized, competency-based system that meets the diverse needs of all learners. Establishing a culture of collaboration that promotes academic excellence, creativity and problem solving is critical. In addition, leaders must empower teachers to effectively utilize technology and digital resources, foster community support for innovative approaches, and employ best practices to bring about the changes necessary to support the institution's growth and success.

3. Data and Methodology

Bibliographic data for bibliometric analysis was extracted from the WoS CC. WoS CC is commonly used for bibliometric analysis, as it is a comprehensive database covering over 22000 journals and 8 citation indexes, including Social Science Citation Index or SSCI [25]. The bibliographic data is based on topic search using the query “blended learning” OR “blended teaching”. The topic search restricts the search of the keywords to titles, abstracts and keywords. The bibliographic data set was restricted to the period of the COVID-19 pandemic and post the COVID-19 pandemic, ranging from 2020 to 2023. The bibliographic data was further restricted to peer-reviewed publications, namely articles and review articles, written in English. There were 5810 studies left for bibliometric analysis.

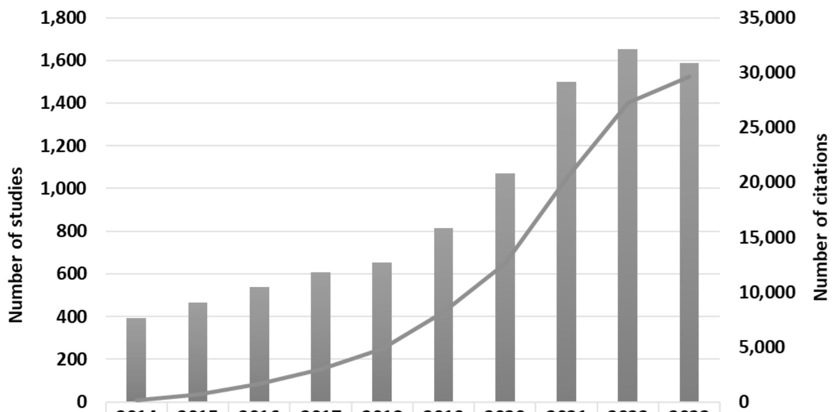
Two software tools are used for bibliometric analysis. VOSviewer is a software commonly used for bibliometric analysis and visualisation of bibliometric networks, and R with the package “bibliometrix” allows performing a variety of bibliometric analyses that complement the results of VOSviewer [26], [27]. The nodes in the bibliometric networks visualised by VOSviewer represent the elements to be analysed, namely countries, organisations, journals, publications, or keywords, while the thickness between elements represents their relatedness based on co-authorship and co-occurrence analysis or bibliometric coupling analysis. The nodes are also divided into clusters by colours. We plot the annual publication and citation counts and provide summary statistics of the extracted publications, on which we then perform various bibliometric analyses.

First, we are interested in cooperation between countries and organisations. We present the most productive countries in terms of number of publications and visualise co-authorship both in a bibliometric network and on a world map. Next, we present the most productive organisation and a bibliometric network that visualises the co-authorship between organisations. Second, we perform a bibliometric coupling analysis for journals and publications. The links in the bibliometric coupling analysis are based on mutual references in publications. Therefore, bibliometric coupling analysis is more appropriate than co-citation analysis when examining relatively recent publications because their citations have not yet accumulated sufficiently compared to older publications [28]. We present the most productive journals in the area. Third, we focus on keywords and perform a keyword co-occurrence analysis. We present the most frequently occurring author keywords and keywords plus, specifically for the WoS CC database. Keywords plus represent keywords extracted from the titles of referenced studies and are a valuable resource when investigating the most frequently occurring topics underlying the references. Lastly, we present the most cited publications together with the bibliometric network of publications organised in clusters by topics. We also provide a content analysis of the most influential publications.

4. Results

4.1. Overview of the Research Area

The field of blended teaching and learning grew rapidly during the years of the COVID-19 pandemic and post the COVID-19 pandemic. Before limiting the publications to the stated period, we present the total number of publications and the total number of citations of all research articles and reviews written in English on the topic of blended teaching and learning in the last ten years. There are a total of 9285 publications on the topic of blended teaching and learning with a total of 120504 citations. We present the last ten years graphically in Figure 1. The number of publications has increased over the last ten years, with an even greater increase in citations. If we restrict the studies to the period of the COVID-19 pandemic and post the COVID-19 pandemic (2020-2023, we obtain 5,810 publications, which is more than 60% of the total publications on blended teaching and learning in the last ten years.



	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Number of studies	394	466	539	606	655	815	1,070	1,498	1,653	1,589
Number of citations	167	695	1,648	3,007	4,843	8,191	12,602	20,443	27,230	29,606
Average citation number	0.42	1.49	3.06	4.96	7.39	10.05	11.78	13.65	16.47	18.63

Figure 1. Number of publications and citations on the topic of blended teaching and learning, 2014-2023, Source: authors

The importance of blended learning is underscored by the extreme increase in citations of publications published during the years of the COVID-19 pandemic. In 2020, there were 1070 publications with 12608 citations; in 2021, there were 1498 publications with 20443 citations. The peak publication count was reached in 2022 with 1653 publications and 27230 citations, while the peak citation count was reached in 2023 with 1589 publications and 29606 citations (Figure 1). From 2020 to 2021, after the first year of the pandemic, the number of publications increased by a solid 40% and the number of citations increased by about 62%. The average number of citations per publication increased from 11.78 citations per publication in the first year of the pandemic, 2020, to 18.63 in 2023.

While the number of publications increased during the pandemic years, the increase in citations is more pronounced, and the increase in the post-pandemic research is even more evident. Comparing the year before the pandemic, 2019, to 2022, the number of publications increased by about 69% (from 815 to 1653). Comparing the number of citations in 2019 to 2023, the number of citations increased by about 232.44% (from 8191 to 27230). The increase in publications and citations underscores the research interest and importance of the field, and the true significance of these studies is becoming more apparent in the years following the COVID-19 pandemic.

Next, we present the summary statistics of the publications included in the bibliometric analysis (Table 1). The publications came from more than 130 countries. There were more than 5800 affiliations from almost 20000 authors. The publications were published in more than 2100 journal titles by more than 540 publishers.

Countries	135
Affiliations	5849
Authors	19999
Journal Titles	2179
Publishers	548
Research Areas	147
Author Keyword	14648
Keyword Plus	5927

Table 2. Summary statistics, source: authors, using WoS CC database

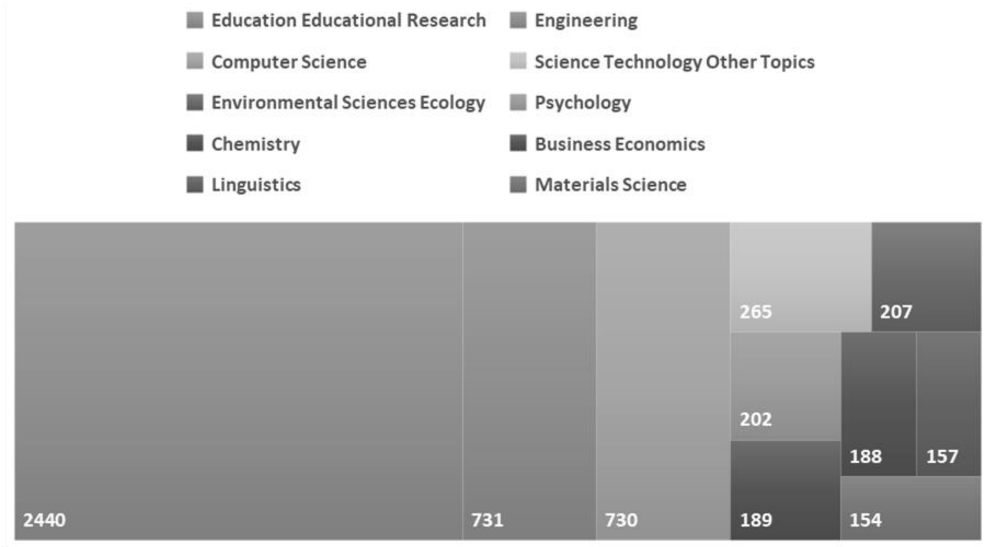


Figure 2. Ten research areas with the most publications, source: authors, using WoS CC database

The five most productive publishers included Elsevier, followed by Springer Nature, Taylor & Francis, MDPI, and finally, Wiley. Most publications on blended learning were indexed in the Science Citation Index Expanded (SCI-E) (2476), the Emerging Sources Citation Index (ESCI) (2217), and finally the Social Sciences Citation Index (SSCI) (1722). The topics of the publications were assigned to one of the 147 research areas. The ten research areas with the highest number of publications are shown in Figure 2. As expected, the first research area with the most publications is Education Educational Research (2440), followed by Engineering (731) and Computer Science (730).

4.2. Countries and Organisations

First, we present the countries that published the most publications on blended teaching and learning during and post the period of the COVID-19 pandemic. The United States of America (USA) was the most productive country with 1001 publications and 9150 citations. China was second with 970 publications and 8767 citations. The third-ranked country was England with 449 publications and 3791 citations. The ten countries with the most publications are listed in Table 2 together with the corresponding citation numbers.

Countries / Regions	Number of Publications	Number of Citations
United States	1001	9150
China	970	8767
England	449	3791
India	395	2574
Australia	385	3845
Canada	244	2337
Germany	242	2415
Spain	241	2176
Saudi Arabia	206	2610
South Africa	172	676

Table 2. Most productive countries, source: authors

The bibliometric network of countries based on the co-authorship analysis is shown in Figure 3. The size of the nodes corresponds to the number of publications of each country. The links indicate the collaborations between countries. Furthermore, the countries are divided into three groups based on the analysis of co-authorship. The red group at the left side of the network is mainly composed of European countries, and the green group is composed of the most productive countries such as the United States and Australia, as well as China and some other Asian countries. The blue group consists mainly of African countries and India. Figure 4 shows the world map of collaborations.

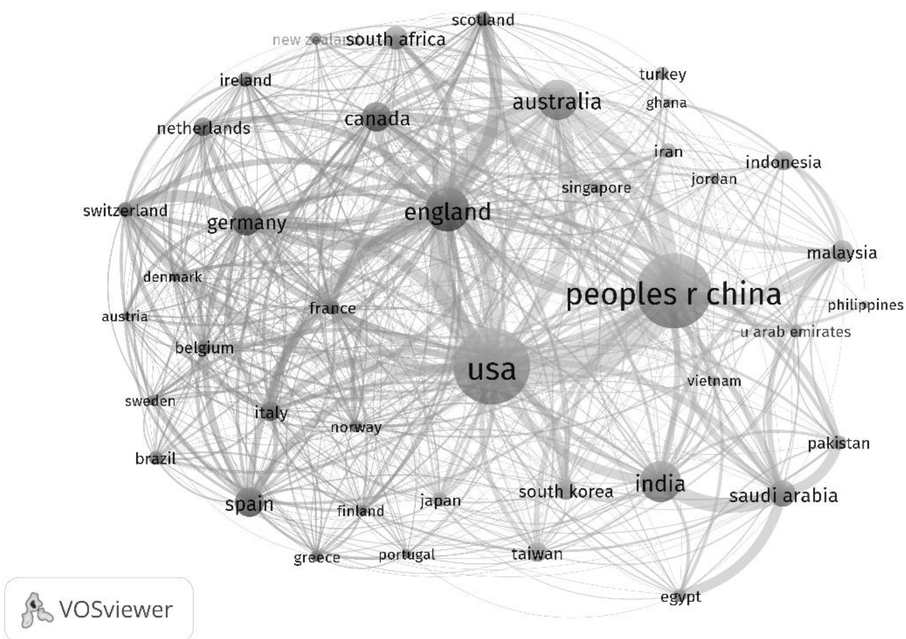


Figure 3. Network of countries based on co-authorship analysis, source: authors

The organisations that were most productive on the topic of blended teaching and learning were universities: Monash University, University College London, Griffith University and University of Edinburgh (Table 3). With the exceptions of University of Edinburgh, all universities were from the most productive countries.

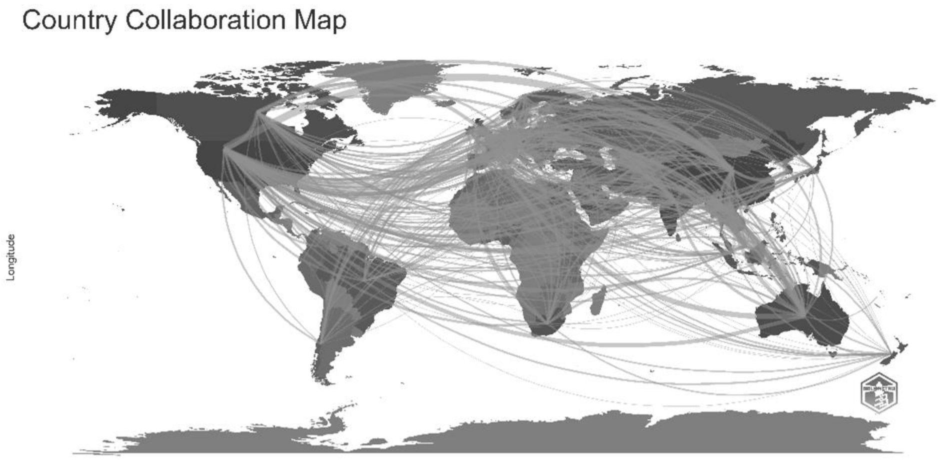


Figure 4. Collaboration network shown on the world map, source: authors

Organization	Country	Number Of Publications	Number Of Citations
Monash University	Australia	35	296
University College London	England	34	432
University of Edinburgh	Scotland	32	570
Griffith University	Australia	32	221
Zhejiang University	China	32	444
University of British Columbia	Canada	31	496
University of Melbourne	Australia	31	214
University of Toronto	Canada	31	452
Chinese Academy of Sciences	China	29	452
King Saud University	Saudi Arabia	29	377

Table 3. Most productive organizations, source: authors

4.3. Journals

The ten most productive journals are listed in Table 4. The publishers of the most productive journals include MDPI (3), Frontiers (2), and Springer (2). The most productive journals are Education Sciences, followed by Education and Information Technologies and Sustainability. The most productive journals are mainly focused on education, learning and technologies, and health-related fields.

Journal	Publisher	Number of Publications	Number of Citations
Education Sciences	MDPI	123	1248
Education And Information Technologies	Springer	110	1482
Sustainability	MDPI	82	580
BMC Medical Education	Springer Nature	75	756
International Journal of Emerging Technologies in Learning	IAOE	66	530
Frontiers in Psychology	Frontiers	65	511
IEEE Access	IEEE	59	423
Frontiers in Education	Frontiers	53	428
Interactive Learning Environments	Taylor & Francis	45	370
Applied Sciences	MDPI	38	265

Table 4. Most productive journals, source: authors

The network of journals based on bibliometric coupling analysis groups the journals into three groups (Figure 5). The largest, red cluster at the top and middle of Figure 5 includes journals on education in general and technology in education. The blue cluster further to the right comprises journals from the field of engineering sciences, while the green cluster on the bottom includes journals in the field of health and medical education. The number of medical education journals, which are also among the most productive journals, underscores the importance of blended learning in health-related education, especially during the period of the COVID-19 pandemic.

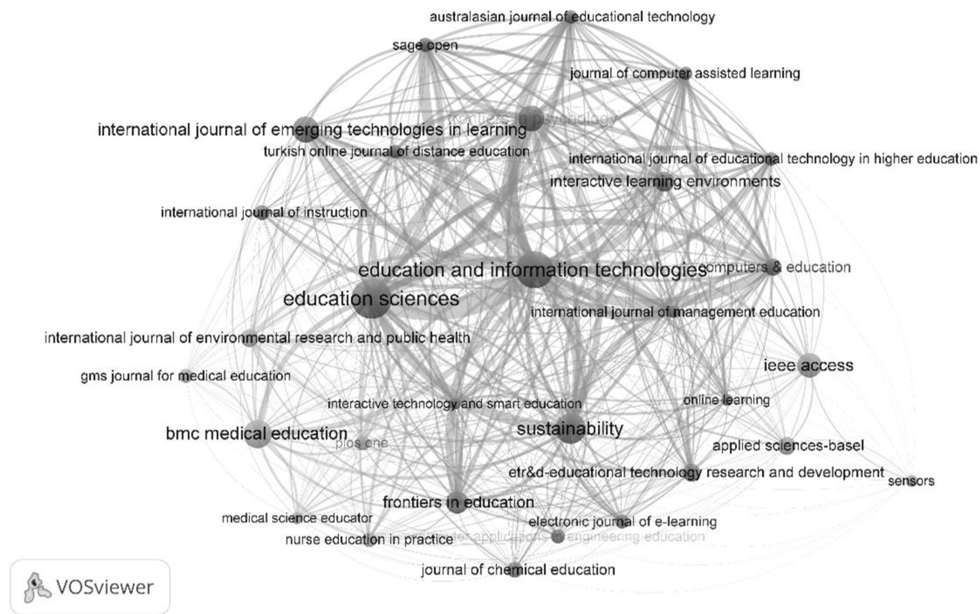


Figure 5. Bibliometric network of Journals based on the bibliometric coupling analysis, source: authors

4.4. Keywords Analysis

In the next step of our analysis, we examine the keywords used in publications on blended teaching and learning. Table 5 lists the most frequently occurring author keywords and keywords plus. The most common author keyword is blended learning, followed by COVID-19, higher education, and several keywords that refer to different forms of online education, such as online learning and e-learning, making different forms of online learning the focus of publications. There are also several other keywords related to broader terms of teaching and learning using ICT, such as online teaching and online education and distance learning and distance education. Flipped classroom, a special form of blended learning, is also among the 20 most frequently occurring keywords. Medical education is also highlighted among the most frequently occurring keywords. Among the keywords plus, which are the keywords extracted from the references of the publications, the most frequently occurring keywords were education, students, and online. In addition, there are several keywords related to online education experiences, such as performance, impact, perception, satisfaction, engagement, motivation, and skills, which emphasise the importance of online education experiences and attitudes toward online education. Higher education was among the most frequently occurring keywords in both keyword types, underscoring the recognised importance of research in this area in higher education.

The topics found through keyword analysis are consistent with the literature review, which highlighted the variety of terms used in the field, the importance of learner experiences, and the prevalence of research in higher education institutions.

Author keywords		**Keywords Plus**	
Keyword	**Occurrences**	**Keyword**	**Occurrences**
blended learning	1442	education	565
covid-19	453	students	483

higher education	337	online	396
online learning	336	performance	384
machine learning	323	model	312
e-learning	270	impact	295
deep learning	222	perceptions	243
education	199	technology	235
flipped classroom	133	higher education	222
distance learning	114	design	207
medical education	111	satisfaction	185
artificial intelligence	91	knowledge	169
covid-19 pandemic	87	engagement	168
online education	80	skills	141
learning	78	science	138
active learning	76	motivation	137
training	73	framework	133
student engagement	71	achievement	128
distance education	66	classroom	125
learning analytics	66	teachers	111

Table 5. 20 most occurring author keywords and keywords plus, source: authors

Keywords were connected in a bibliometric network based on keyword co-occurrence (Figure 6).

We describe the clusters based on their colour. On the one hand, the green cluster, at the top of Figure 6, contains keywords related to participant (student) perceptions related to blended teaching and learning: engagement and motivation, participant experiences and satisfaction, as well as participant performance, self-efficacy, and achievements and outcomes. On the other hand, the red cluster covers different aspects of blended teaching and learning from the teaching point of view – curriculum, challenges, knowledge, skills, technology, pedagogy. The red cluster also contains keywords related to different types and synonyms of online learning, teaching and education, such as distance learning, e-learning, and flipped classroom. There is also a strong link between blended learning with higher education and university teaching in both the green and the red cluster. The blue cluster at the right side of Figure 6 refers to keywords related to emerging digital technologies such as machine learning, deep learning, and artificial intelligence, as well as related keywords such as model, prediction, classification, system and design.

The clusters show how research on teaching and learning with ICT is intertwined with education-related keywords in general and participants' and learners' perceived experiences of teaching and learning.

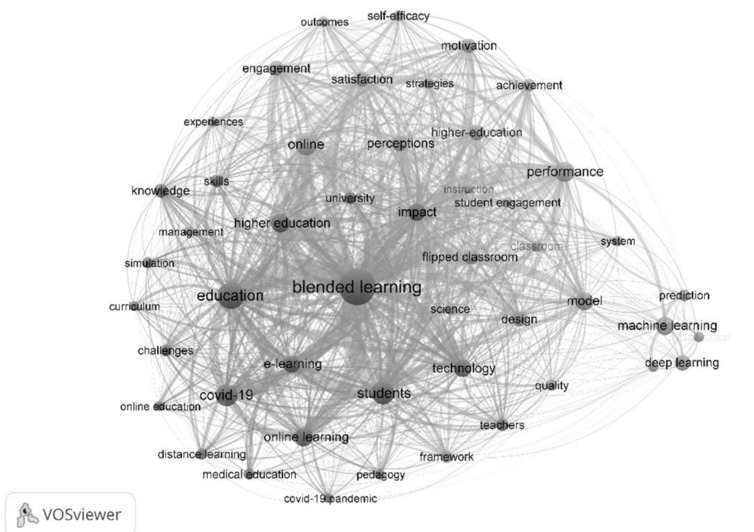


Figure 6. Network of keywords based on co-occurrence analysis, source: authors

4.5. Publications

As a final point of our analysis, we present the most frequently cited publications and provide a content analysis of these publications. The most frequently cited publications focused primarily on student perspectives and challenges, recommendations, and frameworks related to blended learning. The publications that focused on student perspectives examined attitudes toward online learning and student performance and engagement in online courses. In addition, publications that addressed frameworks, challenges, and recommendations also addressed strategies for delivering online education, success factors, digital literacy, and digital competence of teachers. In addition, several publications compared traditional learning methods and experiences with online education. Almost all of the most frequently cited articles dealt with publications related specifically to the COVID-19 pandemic. The ten most frequently cited publications also included three literature reviews and one framework study (Table 6).

Title	Author, year	Total Citations
Knowledge, Attitudes, Anxiety, and Coping Strategies of Students during COVID-19 Pandemic	Baloran, 2020	389
Challenges in the online component of blended learning: A systematic review	Rasheed, Kamsin and Abdullah, 2020	382
Building Effective Blended Learning Programs	Singh, 2021	346
Emergency remote teaching and students' academic performance in higher education during the COVID-19 pandemic: A case study	Iglesias-Pradas et al., 2021	277
Mapping research in student engagement and educational technology in higher education: a systematic evidence map	Bond et al., 2020	248
Challenges to Online Medical Education During the COVID-19 Pandemic	Rajab, Gazal and Alkattan, 2020	234
From digital literacy to digital competence: the teacher digital competency (TDC) framework	Falloon, 2020	211
Blended Learning Compared to Traditional Learning in Medical Education: Systematic Review and Meta-Analysis	Vallee et al., 2020	205
E-Learning Critical Success Factors during the COVID-19 Pandemic: A Comprehensive Analysis of E-Learning Managerial Perspectives	Alqahtani and Rajkhan, 2020	200
Student perspective of classroom and distance learning during COVID-19 pandemic in the undergraduate dental study program Universitas Indonesia	Amir et al., 2020	186

Table 6. The ten most cited publications, source: authors

The most frequently cited publications from the observed period deal with the problem of absorbing course contents from the students' point of view and the way the same content is taught from the professor’s point of view, thus highlighting the most common problems during the demanding process of receiving and teaching from psychological, technical, and pedagogical points of view.

The challenges were primarily related to the acceptance of new technologies in education and the delivery of education in an online environment, such as the challenges related to self-regulation, the challenges of delivering medical education in an online environment, and the challenges faced by teachers as a result of new teaching methods. Rasheed and colleagues [17] also found that challenges with self-regulation and the use of learning technologies were the biggest challenges students faced. They also distinguished the challenges teachers face and concluded that they are mainly in the use of technology for teaching. The biggest challenges for educational institutions are providing appropriate instructional technologies and effective support for teacher training.

Some of the most influential publications showed that students had sufficient knowledge and perception of the high health risk during the COVID-19 pandemic and were therefore satisfied with the government's preventive measures of social distancing and restriction of social contact. However, it was also found that online approaches to teaching and learning in various forms, such as e-learning and blended learning, were not well received by the students [29]. Amir and colleagues emphasise that the COVID-19 pandemic is changing not only the use of technology in education but also the educational strategies of the future. Despite some challenges, students were able to adapt to the new learning methods of distance learning and the majority agreed that blended learning, meaning combining face-to-face and online learning, can be implemented in the future [30]. Support for emergency distance learning was also found in a case study by Iglesias-Pradas and colleagues in which students' academic performance improved during emergency distance learning. No difference was found between courses with different teaching methods or class sizes. Students supported the idea that organisational factors can contribute to the successful implementation of emergency distance education, and the study discussed considered various organisational, individual, and instructional aspects of distance education [31].

A systematic review of the use of digital technologies in higher education provided an evidence map that forms the basis for further research into the discipline-specific use of technology to promote student engagement. Behavioural engagement was by far the most frequently identified dimension related to educational technology use, followed by affective and cognitive engagement [32]. The key enablers for the future use of technology in the classroom are the digital literacy of students and teachers needed to work productively in the new digitised environments while ensuring safety and ethics [33]. Alqahtani and Rajkhan found that technology management, management support, student awareness of the use of e-learning systems, and demand for high levels of information technology by lecturers, students, and universities were the most influential factors for e-learning during the period COVID-19 [34]. Readiness to adopt e-learning played an important role in promoting the educational process during the COVID-19 pandemic. Among the five learning systems studied, blended learning proved to be the most suitable learning system. Blended learning also showed better impact on knowledge outcomes compared to traditional learning in education.

Medical and health education was of particular interest during the COVID-19 pandemic. Rajab and colleagues concluded that the COVID-19 pandemic could have a positive impact on some factors of medical and health-related education, but also pointed to numerous challenges that arose in terms of social life, finance, and research [35]. In the area of medical and health-related education, the development of online simulators, virtual hospitals and virtual case studies, as well as various forms of telemedicine, may help to promote virtual education. A systematic review of blended learning compared to traditional learning in medical education consistently found better results in learning outcomes for blended learning [36].

The publications can further be grouped into four clusters of publications basis of a bibliometric coupling analysis, in which the references in the publications are taken into account when creating bibliometric links (Figure 7).

Based on a content analysis, the red cluster focuses mainly on publications related to the COVID-19 pandemic, such as the adoption of online education technologies as an emergency measure for providing education during the COVID-19 pandemic. The green cluster focuses on blended learning from the teacher perspective, tackling challenges, strategies, and skills needed to deliver high quality learning experience and also contains several literature reviews, including publications on bibliometric analysis. The blue mainly containts publications that deal with reviews on students' attitudes towards self-regulated learning, online courses, with some of the articles focusing on nursing students particularly. The yellow cluster contains publications that consider participant or student engagement and satisfaction, strategies for online education and support for online education delivery.

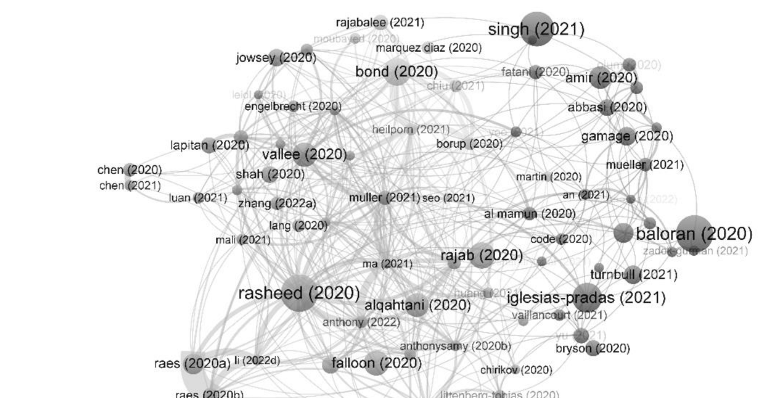


Figure 7. Bibliometric network of publications based on the bibliometric coupling analysis, source: authors

5. Discussion and Conclusion

As elaborated in previously, “blended learning” is not a term coined for teaching in the COVID-19 pandemic. Blended learning represents one of the forms for technologically supported teaching and learning and has been a topic of interest to researchers and teachers for more than a decade. However, the COVID-19 pandemic served as a catalyst to accelerate the adoption of ICT solutions in the classroom. Now that it is known that there are viable and affordable alternatives to traditional teaching methods, that educational institutions are already equipped with some technological solutions, and that teachers and educational institutions have experience using them, it might be argued that there will not be a complete return to the old methods. Perhaps technology is here to stay. If adopted by smaller universities as a part of their educational management efforts to better compete with larger or closer universities, ICT solutions such as blended learning may even be seen as disruptive innovations that will lead to further globalisation of education [37]. In addition to increasing competition among educational institutions, these disruptive innovations may also help provide needed and more affordable education to potential students who live far from universities (e.g., on islands, in rural or other remote areas). While the education sector during the COVID-19 pandemic period relied heavily on online learning approaches and methods, the interest in ICT-enhanced education also spilled over into the scientific community, providing an opportunity to examine influences, factors, and mechanisms in more detail.

Scientific interest in publishing research on blended learning is steadily increasing over the last decade. This trend accelerated from 2020 to 2023 due to the effects of the COVID-19 pandemic and the need for urgent uptake of teaching and learning in an online environment. The importance of research in this area is supported by the sharp increase in citations of publications. Although there are several geographic and institutional centres that produce much of the research on blended learning, the topic is globally significant, as evidenced by the large number of authors, journals, affiliations and countries contributing to the field. The most productive countries are USA, China, England, India and Australia, and the most productive universities, namely Monash University, University College London, Griffith University, University of Edinburgh, and Zhejiang University mostly pertain to the most productive countries. The most productive journals are Education Sciences, followed by Education and Information Technologies, Sustainability, BMC Medical Education and International Journal of Emerging Technologies in Learning.

The most productive journals are mainly focused on educational research, using technologies for learning, and health-related fields. The most used keywords were blended learning and COVID-19, followed by higher education, online learning and e-learning. Higher education as an important topic across the are is indicating that members of academia are well aware of the need and presence of blended learning in their environment. Furthermore, several keywords that refer to different forms of online learning, and broader terms related to teaching and learning using ICT. Medical education is also highlighted among the most frequently occurring keywords. There are several keywords emphasising the importance of online education experiences and attitudes toward online education, such as performance, impact, perception, satisfaction, engagement, motivation, and skills. The keywords use is in line with the literature reviewed and the topics of the most influential publications. The most influential publications addressed student perspectives, the challenges to teachers and challenges to institutional adoption of various forms of online learning, and recommendations and frameworks for online education and blended learning, and higher education.

Of particular interest were student and learner attitudes toward online learning, their experiences, performance, and engagement in online courses. Most publications were related to the higher education sector and focused on students, teachers, institutions, and their experiences with blended learning during the pandemic. In addition to exploring the challenges of online education from several perspectives, the publications also addressed strategies for providing online education, success factors, and teacher and student digital competence and literacy as the skills needed in a digital environment. Some of the major obstacles to implementing blended learning methods in classrooms were the lack of ICT and the lack of knowledge about how to use the new technology. However, these barriers were quickly overcome in the COVID-19 period as education systems in Europe and most other parts of the world moved to some form of e-learning. The challenges of delivering online education lie not only in the digital literacy of all involved, but also in uncertainty about the impact of the new teaching methods on the quality of the curriculum and the quality of learning in general. Concerns about blended learning and other types of online learning approaches include the likely loss of social interaction and soft skills, the additional administrative burden teachers face in an online environment, and the lack of effective control in knowledge assessment. Furthermore, if technology and blended learning lead to a shift in the role of teachers from that of lecturer to that of knowledge facilitators, this could be seen as a devaluation of the teaching profession. Several publications have therefore compared traditional learning methods and experiences with blended learning and similar approaches, and some have concluded that blended learning provides better results in learning outcomes.

The main contribution of this paper is to highlight the importance of blended learning as one of the technological advances in education, especially during the COVID-19 pandemic. The purpose of this research is to provide a knowledge base on the findings and advances in the extensive research on blended learning during the COVID-19 pandemic, providing indicators of the most productive countries and organisations, the most important journals in the area, the main topics and findings, thus providing an overview and aid in promoting further research in the area. Therefore, blended learning is not only considered as a here-to-stay teaching practise, but also as a branch of educational management research that is vivid of scientific research. Transformation from traditional to blended learning seems inevitable and should not be left to itself, i.e. it should be carefully managed. In these efforts, educational management should be planned and administered in a way that promotes excellence, prepare teachers to not just adapt to new technological requirements but also to shift to transform teaching into a personalized, competency-based system that meets the diverse needs of all learners.

The main limitation of this work is that it focuses mainly on blended learning as one of the approaches to online learning. Moreover, the bibliometric analysis is limited by the choice of keywords and the choice of database, language and type of study. Future research should focus on the long-term trends and development of blended learning and other online learning approaches in general in the post-pandemic period. In addition, future research in this area could gather the experiences of learners, educators, and institutions during the COVID-19 pandemic and synthesise key findings, leading to the creation of a comprehensive theoretical framework for blended learning.

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Proactive Detection of Malicious Webpages Using Hybrid Natural Language Processing and Ensemble Learning Techniques

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ABSTRACT

The proliferation of malicious webpages presents a growing threat to online security, necessitating advanced detection methods to mitigate risks. This paper proposes a novel approach that integrates Natural Language Processing (NLP) techniques with an ensemble of machine learning models for the proactive detection of malicious web content. By leveraging semantic analysis, lexical patterns, and metadata extraction, the proposed framework enhances the identification of suspicious patterns in web page content. The ensemble model combines decision trees, random forests, and gradient boosting methods, optimizing classification accuracy and reducing false positives. A comprehensive evaluation using a large dataset of web pages, including both benign and malicious examples, demonstrates the superiority of the proposed method over traditional single-model approaches. With accuracy rates exceeding 98%, this framework achieves a robust, scalable solution for real-time web content analysis, providing a critical tool for cybersecurity professionals to detect and block malicious webpages before they can cause harm. Future directions include the integration of deep learning architectures and adaptive filtering techniques to further refine detection capabilities.

Keywords: Count, Term frequency and Inverse document frequency, Machine learning model, Phishing, Malicious webpages

1. Introduction

The rapid expansion of the internet has revolutionized communication, business, and information sharing, but it has also introduced significant security threats. Malicious webpages are among the most pervasive forms of cyber threats, used by attackers to spread malware, launch phishing attacks, and steal sensitive information. These pages often masquerade as legitimate sites, deceiving users into disclosing personal data or infecting their systems with malicious software. As web usage continues to increase globally, the detection and prevention of such threats have become critical components of cybersecurity strategies. Traditional web filtering systems based on URL blacklists, signature matching, or rule-based methods are no longer sufficient due to the dynamic and evolving nature of malicious webpages. Attackers continuously modify their methods, including changing URLs, obfuscating content, and employing sophisticated evasion techniques that can bypass conventional detection systems. Consequently, there is a pressing need for advanced, intelligent systems that can effectively analyze and classify web content in real-time, ensuring that malicious webpages are identified before they cause harm [1-4]. Recent advancements in artificial intelligence (AI) and machine learning (ML) have opened new avenues for detecting and preventing these threats. Natural Language Processing (NLP), a subfield of AI, offers promising techniques for analyzing the textual content of webpages, identifying semantic patterns, and detecting anomalies that may indicate malicious intent. NLP allows the system to analyze not only the structure and syntax of a webpage but also its context, meaning, and underlying intent. Combining NLP with machine learning models enables the development of systems that can adapt to new and evolving threats, going beyond the limitations of static rules or predefined signatures. This approach leverages a more holistic analysis of web content, considering multiple dimensions such as lexical features, syntactic structure, sentiment analysis, and even the metadata associated with the page, such as domain age and source credibility [5-7].

Machine learning models, particularly ensemble methods, have demonstrated their effectiveness in various classification tasks, including cybersecurity applications. These models, which combine the strengths of multiple classifiers, have been shown to improve accuracy and reduce false positives by balancing the weaknesses of individual algorithms. In the context of web content analysis, ensemble learning can enhance detection by integrating various perspectives on the features extracted from a webpage [8-12]. For instance, decision trees can capture hierarchical relationships between features, random forests can provide robustness through random feature selection, and gradient boosting can improve model accuracy by correcting the errors of weaker models. This fusion of machine learning techniques with NLP-driven content analysis offers a comprehensive solution to the challenges posed by malicious webpages.

However, despite these advancements, existing methods often struggle with a few key limitations. First, many models rely heavily on predefined feature sets that may not fully capture the complexity of malicious content. Attackers often use obfuscation techniques, such as encoding malicious scripts or dynamically generating webpage content, making it difficult for static feature-based models to detect these threats. Additionally, many models focus primarily on the URL or metadata of a webpage, neglecting the rich information available in the webpage's content [13-15]. While URL-based detection methods can be effective in certain scenarios, they are often easily circumvented by attackers who can rapidly generate new URLs or use URL shortening services to hide their intent. As a result, there is a growing consensus that content-based detection methods, which analyze the actual substance of a webpage, are critical to improving the detection of malicious webpages. Another limitation of current approaches is their focus on specific types of malicious webpages, such as phishing sites or malware distribution pages, without considering the broader landscape of threats. A more generalized approach that can classify various types of malicious webpages is essential to create a more resilient cybersecurity framework. Furthermore, many existing systems are not designed to operate in real-time or at scale, limiting their effectiveness in large, dynamic environments such as corporate networks or global internet infrastructure [16-17]. Given the growing number of webpages created each day and the increasing sophistication of cyber-attacks, it is essential to develop systems that can operate at scale, processing large volumes of web content in real-time to provide timely protection against emerging threats. In this paper, we propose a novel framework that integrates NLP methods with an ensemble of machine learning models for the effective analysis of web content to classify malicious webpages. Our approach addresses the limitations of existing models by employing a hybrid methodology that combines lexical, syntactic, and semantic analysis with advanced machine learning techniques. This framework leverages NLP to extract meaningful features from the textual content of webpages, including keyword frequency, sentiment analysis, and semantic relationships, which are then fed into a machine learning ensemble for classification. The ensemble model consists of multiple classifiers, including decision trees, random forests, and gradient boosting, each of which brings a unique perspective to the classification task. By combining the outputs of these classifiers, our system achieves high accuracy and robustness in detecting a wide variety of malicious webpages, including phishing sites, malware distribution pages, and fraudulent websites.

One of the key innovations of our approach is the use of a dynamic feature extraction process, which allows the system to adapt to new types of threats by continuously updating its feature set based on the evolving characteristics of malicious webpages. This dynamic process ensures that the system remains effective even as attackers modify their methods to evade detection. In addition, our framework is designed to operate at scale, capable of processing large volumes of web content in real-time. This scalability is achieved through the use of parallel processing techniques and distributed computing, which enable the system to analyze multiple webpages simultaneously without compromising performance.

To evaluate the effectiveness of our proposed framework, we conducted extensive experiments using a large dataset of web pages, including both benign and malicious examples. The dataset was collected from multiple sources, including publicly available web repositories and specialized datasets containing known malicious webpages. Our experiments focused on evaluating the classification accuracy, false positive rate, and scalability of the system. The results demonstrate that our approach significantly outperforms traditional single-model methods, achieving an overall classification accuracy of over 98%. In addition, the system was able to maintain low false positive rates, ensuring that legitimate webpages are not incorrectly flagged as malicious. These results highlight the potential of our framework to provide a robust, scalable solution for the detection of malicious webpages in real-world environments.

Our contributions in this paper are threefold: First, we introduce a novel framework that integrates NLP techniques with an ensemble of machine learning models to improve the detection of malicious webpages. Second, we develop a dynamic feature extraction process that allows the system to adapt to evolving threats, ensuring long-term effectiveness. Third, we demonstrate the scalability of our approach, showing that it can operate in real-time and at scale, making it suitable for large networks and internet infrastructure. The proposed framework not only enhances the detection accuracy of malicious webpages but also provides a flexible, adaptive solution that can keep pace with the rapidly changing landscape of cyber threats. This research represents a significant step forward in the development of intelligent systems for web security, with potential applications in both enterprise and consumer settings.

2. RELATED WORKS

The detection of malicious web traffic has become a crucial area of study due to the increasing sophistication of cyber-attacks, especially those that target sensitive information and critical infrastructure. Traditional security measures, such as static rules or blacklist-based systems, are no longer sufficient to combat these evolving threats. Modern approaches rely on advanced machine learning (ML) and natural language processing (NLP) techniques to enhance real-time malicious traffic detection by analyzing various features, including lexical content, metadata, and network behaviors. This section reviews key literature relevant to online machine learning techniques, deep learning models, and their applications in malicious traffic detection, particularly focusing on innovations in web content analysis.

A wide range of studies has explored the use of online machine learning for network traffic analysis. Shahraki et al. (2022) conducted a comparative analysis of online machine learning techniques for analyzing network traffic streams, highlighting the growing need for real-time, adaptive models in cybersecurity. Their work emphasized the limitations of batch learning models, which often struggle to cope with the dynamic nature of internet traffic. The study explored various online learning algorithms that allow models to update incrementally as new data becomes available, ensuring the system remains up-to-date with the latest threats. The research concluded that online machine learning offers significant advantages in scalability and responsiveness, which are essential for mitigating real-time threats such as malicious webpages.

Further advancing the field, Zhang et al. (2023) proposed a real-time malicious traffic detection system utilizing the online isolation forest algorithm over software-defined wide-area networks (SD-WAN). This method demonstrated the efficiency of real-time anomaly detection in dynamic network environments, where traditional detection mechanisms often fail to scale effectively. By using the isolation forest, the model was able to detect anomalies in encrypted traffic streams, enhancing its ability to identify malicious activities. This approach is particularly relevant to web-based attacks, where malicious behavior can be hidden within encrypted traffic to evade traditional inspection methods.

Graph-based approaches have also been instrumental in improving detection techniques, as highlighted by Hong et al. (2023), who proposed a hybrid analysis framework combining graph-based methods with multi-view feature extraction for encrypted malicious traffic detection. By treating network traffic as a graph of interconnected nodes, this approach allowed for the detection of more complex and camouflaged malicious behaviors. Their framework focused on encrypted traffic, which is increasingly used to mask malicious activity, and applied graph-based analysis to detect traffic anomalies by examining the relationships between different traffic flows. This work complements traditional machine learning methods by adding a layer of complexity that can improve the identification of deeply obfuscated threats.

Wang and Thing (2023) made significant contributions by investigating the role of feature mining in encrypted malicious traffic detection using deep learning and traditional machine learning algorithms. Their work demonstrated that deep learning models, particularly convolutional neural networks (CNNs), are highly effective in capturing complex patterns in encrypted traffic that traditional models might miss. They explored how different features, such as packet size, timing, and frequency, can be extracted from encrypted streams and used to train models that identify malicious behaviors with high accuracy. Their research also pointed out that combining deep learning with traditional machine learning algorithms, such as decision trees or support vector machines (SVMs), can further enhance the robustness of detection systems.

Another innovative approach was proposed by Fang et al. (2021), who developed a communication-channel-based method for detecting deeply camouflaged malicious traffic. Their model focused on analyzing the communication patterns between nodes in a network to detect anomalies that might indicate malicious activity. This method was particularly effective in identifying threats that rely on stealth and obfuscation, as it focused on communication behaviors rather than the content of the traffic itself. By observing how different nodes interact and detecting irregularities in these patterns, the model was able to flag suspicious behavior even when the content of the traffic was encrypted or disguised.

Several studies have explored machine learning's role in detecting encrypted malicious traffic in more detail. Wang et al. (2022) conducted a comprehensive study of various machine learning approaches, datasets, and techniques for encrypted malicious traffic detection. Their comparative study examined the efficacy of several algorithms, including deep learning models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, which are capable of processing sequential data like network traffic streams. Their findings showed that, while deep learning models are highly effective in detecting encrypted malicious traffic, they require extensive computational resources and are often difficult to implement in real-time scenarios. Nevertheless, their study highlighted the potential of these models to significantly improve detection accuracy when applied in well-configured environments.

Aljabri et al. (2022) explored the use of lexical, network-based, and content-based features for detecting malicious URLs using machine learning and deep learning models. Their assessment revealed that combining multiple feature types leads to higher detection accuracy compared to using any single type of feature. Lexical features, such as the structure of a URL, were particularly useful in identifying phishing sites, while content-based features, which analyze the actual text on a webpage, helped detect malware distribution sites. This comprehensive feature-based approach aligns with the hybrid techniques used in modern NLP-enhanced models for web content analysis, further supporting the need for multi-dimensional feature extraction in the fight against malicious webpages.

Advanced methods for malicious content detection have also been developed using deep learning techniques like the spider bird swarm algorithm, as shown by Alex and Rajkumar (2021). Their study employed deep belief networks to detect malicious JavaScript, which is often embedded within webpages to execute harmful actions. By using an evolutionary algorithm to optimize feature selection and model training, their approach demonstrated enhanced detection of web-based threats, particularly those utilizing obfuscated or polymorphic JavaScript code. This method provided a flexible solution to a common problem in malicious webpage detection: the dynamic and evolving nature of web content.

Shahrivar et al. (2020) contributed to the detection of phishing attacks using machine learning techniques. Their research applied various ML algorithms, including random forests and decision trees, to identify patterns commonly associated with phishing URLs. By focusing on features like domain name characteristics, URL length, and keyword presence, their model was able to effectively differentiate between legitimate and malicious webpages. The use of ensemble methods, which combine multiple algorithms, was particularly successful in reducing false positives, a persistent issue in phishing detection systems.

Recent developments in natural language processing have also been applied to malicious webpage detection, as demonstrated by Haynes et al. (2021), who developed a lightweight phishing detection system using NLP transformers for mobile devices. Their work focused on analyzing the textual content of phishing emails and webpages, using transformer models to extract semantic meaning and detect fraudulent intent. This approach provided a low-resource solution that could be deployed on mobile devices, making it accessible for broader use. The use of transformers in NLP has proven to be highly effective in understanding complex language patterns, particularly in distinguishing between benign and malicious content.

Table 1 provides a comparative analysis of various machine learning (ML) and deep learning (DL) techniques for detecting malicious traffic and phishing threats. Key findings highlight the scalability and adaptability of online learning algorithms, effectiveness in encrypted traffic detection, and the benefits of hybrid models and transformers in enhancing detection accuracy, especially for complex behaviors.

Finally, Lin et al. (2022) conducted an extensive survey on the use of transformer models in AI and machine learning applications. Transformers have become a key technology in NLP due to their ability to process large amounts of text efficiently, making them ideal for tasks like malicious content detection, where semantic analysis plays a crucial role. The survey highlighted the growing importance of transformers in web security, particularly in detecting phishing attempts, malware distribution, and other forms of cyber threats hidden in web content.

Authors	**Title**	**Focus Area**	**Methods/Techniques**	**Findings**
Shahraki et al. (2022)	A comparative study on online machine learning techniques for network traffic streams analysis	Online machine learning for network traffic analysis	Comparative analysis of online ML techniques	Online learning algorithms offer better scalability and real-time adaptability for

				dynamic traffic streams.
Zhang et al. (2023)	Real-time malicious traffic detection with online isolation forest over SD-WAN	Real-time malicious traffic detection using online isolation forest	Isolation Forest for encrypted traffic detection	Demonstrated effective anomaly detection in real-time SD-WAN environments, improving scalability in encrypted traffic streams.
Hong et al. (2023)	Graph based encrypted malicious traffic detection with hybrid analysis of multi-view features	Malicious traffic detection using graph analysis	Graph-based hybrid analysis of multi-view features	Effective in detecting complex, camouflaged malicious behaviors within encrypted traffic using graph-based models.
Wang & Thing (2023)	Feature mining for encrypted malicious traffic detection with deep learning and other ML algorithms	Feature mining and detection in encrypted traffic	Feature extraction using deep learning and traditional ML algorithms	Deep learning, combined with traditional ML, enhances detection capabilities in encrypted malicious traffic streams.
Fang et al. (2021)	A communication-channel-based method for detecting deeply camouflaged malicious traffic	Detecting camouflaged malicious traffic	Communication-channel-based traffic anomaly detection	Focus on analyzing communication patterns to detect deeply obfuscated malicious traffic.
Wang et al. (2022)	Machine learning for encrypted malicious traffic detection: Approaches, datasets, and comparative study	ML techniques for encrypted malicious traffic detection	Comparative analysis of deep learning models (RNNs, LSTMs)	Deep learning models perform well but require substantial resources for real-time encrypted traffic detection.
Aljabri et al. (2022)	An assessment of lexical, network, and content-based features for detecting malicious URLs using ML and DL models	Detecting malicious URLs using a feature-based approach	Lexical, network, and content-based features analyzed with ML and DL	Multi-dimensional feature extraction leads to higher detection accuracy compared to single-type feature approaches.
Alex & Rajkumar (2021)	Spider bird swarm algorithm with deep belief network for malicious JavaScript detection	Detection of malicious JavaScript	Deep belief network and spider bird swarm algorithm	Demonstrated enhanced detection of obfuscated JavaScript through evolutionary algorithm optimization.
Shahrivar et al. (2020)	Phishing detection using machine learning techniques	Phishing URL detection	Random forests, decision trees	Ensemble methods improve accuracy in detecting phishing URLs while reducing false positives.
Haynes et al. (2021)	Lightweight URL-based phishing detection using NLP transformers for mobile devices	Phishing detection using NLP	Transformer-based NLP analysis for mobile phishing detection	Lightweight NLP transformer models effectively detect phishing on mobile devices, offering a low-resource, high-accuracy solution.

Lin et al. (2022)	A survey of transformers	Transformers in AI and ML applications	Survey of transformer-based architectures	Transformers are highly effective for NLP tasks, including detecting malicious web content via semantic analysis and phishing detection.

Table 1. Summary of Recent

3. PROPOSED SYSTEM

The detection of malicious webpages using machine learning techniques requires not only an effective algorithmic framework but also a robust dataset for training and validation. In this enhanced version of the proposed system, we incorporate additional components such as dataset details, vectorization methods, and two algorithms: one for textual content extraction and another for vectorization. These additions are intended to improve the system's ability to handle various types of malicious activities on webpages and provide insights into its underlying processes. To train and evaluate the proposed system, we utilize multiple datasets consisting of both malicious and benign web traffic and webpage content [17-20]. The datasets are carefully curated to include a wide variety of attack types (e.g., phishing, malware distribution, drive-by downloads) and normal web activities to ensure comprehensive coverage and robustness. The datasets used include both publicly available and synthetically generated data. Table 2 shows the summary of dataset.

Dataset Name	Source	Types of Traffic/Webpages	No. of Instances	Data Types	Year Released
CICIDS2017	Canadian Institute for Cybersecurity	Mixed (Malware, Phishing, etc.)	3,000,000	Traffic, Metadata, Content	2017
PhishTank	Open-Source (PhishTank)	Phishing	500,000	URLs, Webpage Content	Ongoing
Alexa Top Sites	Amazon Alexa	Legitimate	1,000,000	URLs, Webpage Content	Ongoing
SD-WAN Traffic Dataset	Custom Generated for Testing	Malicious Encrypted Traffic	2,500,000	Encrypted Network Traffic	2023
Synthetic Dataset	Generated via Web Scraping	Mixed (Malicious + Benign)	1,500,000	URLs, JavaScript Content	2024

Table 2. Summary of Datasets Used

These datasets contain both raw network traffic and webpage content data (e.g., URLs, HTML, and JavaScript). The malicious samples include known phishing websites, malware-infected pages, and other harmful content flagged by security experts. The benign data comes from widely trusted sites like the Alexa Top Sites.

3.1. Dataset Preprocessing

Each dataset undergoes preprocessing before being fed into the system. For web content data, unnecessary HTML tags, formatting elements, and irrelevant data (such as advertisements) are removed to focus on the core content. For network traffic, the packets are parsed to extract relevant features such as flow duration, packet sizes, and timing intervals, while maintaining encryption privacy (i.e., no packet decryption).

We present a robust and dynamic system for detecting malicious webpages by combining advanced Natural Language Processing (NLP), machine learning, and real-time traffic analysis techniques. The proposed framework effectively handles the complexities of modern web attacks, such as phishing, malware injection, and malicious redirects, by analyzing both the content and network behavior of webpages. The system is designed with a hybrid machine learning model and adaptive learning capabilities to ensure real-time detection and scalability.

System Overview

The proposed system aims to detect malicious webpages by analyzing two primary inputs:

1. **Webpage Content**: Extracted from the HTML and JavaScript code of the webpage. Textual and structural features are used for analysis.
2. **Network Traffic**: Analyzed in real time, including both the metadata and packet-level details.

The system is designed to handle multiple datasets, including both encrypted and unencrypted traffic, allowing it to operate across diverse environments, such as corporate networks, educational institutions, and personal systems.

To provide the system with a robust learning foundation, we utilize a collection of datasets from various sources, including:

1. **CICIDS2017**: A widely used dataset for malicious traffic, including phishing, malware, and benign traffic.
2. **PhishTank**: A repository of phishing URLs, which provides raw web content for phishing site detection.
3. **Alexa Top Sites**: A dataset containing benign websites, used to train the system to recognize legitimate pages.

Each dataset provides unique types of information, including web content (HTML, JavaScript), metadata (URLs, descriptions), and network traffic data. This combination ensures the system is well-prepared to detect a wide array of threats.

3.2. Text Vectorization Methods

In the proposed work, we explore different methods of vectorization of text documents that are crucial for the effective analysis and classification of website content. The vectorization process transforms text data into numerical format, enabling machine learning algorithms to process and analyze the information. Here, we discuss three primary vectorization methods: Count Vectorization, TF-IDF Vectorization, and Hash Vectorization.

1. **Count Vectorization:** Count Vectorization, also known as the Bag-of-Words model, is a straightforward method that converts a collection of text documents into a matrix of token counts. In this approach, each unique word in the dataset corresponds to a feature in the resulting feature matrix. The value at each position in the matrix indicates the number of times a particular word appears in a given document. This method is simple and effective for many text classification tasks; however, it ignores the context and order of words, which may lead to the loss of semantic meaning.

Example:

Given two documents:

- Document 1: "I love cats"
- Document 2: "I love dogs"

2. The count vectorization will produce the following matrix:

Word	Document 1	Document 2
I	1	1
love	1	1
cats	1	0
dogs	0	1

TF-IDF Vectorization: The Term Frequency-Inverse Document Frequency (TF-IDF) vectorization method addresses some of the limitations of Count Vectorization. It not only considers the frequency of words in a document (Term Frequency) but also evaluates the importance of each word across the entire dataset (Inverse Document Frequency). The resulting values reflect how relevant a word is in a particular document relative to its frequency in other documents. This method is particularly useful for identifying distinguishing features in text data and helps reduce the impact of common words that may not contribute significantly to the understanding of the document's content.

Term Frequency (TF) is calculated as:

$$TF(t,d) = \frac{f_{t,d}}{\sum_k f_{k,d}}$$

where $f_{t,d}$ is the frequency of term t in document d and the denominator is the total number of terms in the document.

Inverse Document Frequency (IDF) is calculated as:

$$IDF(t) = \log\left(\frac{N}{n_t}\right)$$

where N is the total number of documents, and n_t is the number of documents containing the term t.

The TF-IDF score is then given by:

$$TFIDF(t,d) = TF(t,d) \times IDF(t)$$

Hash Vectorization: Hash Vectorization is a more advanced technique that employs a hashing function to convert words into a fixed-size vector representation. Unlike Count Vectorization and TF-IDF, which rely on the vocabulary of the dataset, Hash Vectorization uses a hash function to map words directly into the feature space. This method can be particularly advantageous when dealing with large datasets or streaming data, as it avoids the need to store the complete vocabulary in memory. However, the primary drawback is that collisions can occur, meaning that different words may be mapped to the same feature, potentially resulting in loss of information. Suppose we hash words to a feature space of size 5. The words "cats" and "dogs" may both be hashed to the same index in the vector, resulting in a loss of distinct information.

3.3. Preprocessing and Feature Extraction

To effectively analyze the incoming data, it undergoes preprocessing and feature extraction steps to convert raw data into a format suitable for machine learning models. The two main data sources—webpage content and network traffic—require different preprocessing techniques.

Webpage Content Preprocessing

Webpage content (HTML and JavaScript code) is extracted and cleaned to remove unnecessary elements, such as styling tags (<style>), script tags (<script>), and advertisements. We focus on extracting meaningful textual content from metadata, body text, and embedded links.

The extracted content is tokenized, stopwords are removed, and stemming/lemmatization techniques are applied to reduce words to their root forms. The processed content is then used for feature extraction.

Network Traffic Preprocessing

Network traffic data, including packet captures, is preprocessed by extracting relevant features such as flow duration, packet size, time between packets, and the source/destination IP addresses. Encrypted traffic is handled using statistical features rather than the content of the packets themselves, ensuring that user privacy is maintained.

3.4. Feature Extraction and Vectorization

The processed data is transformed into numerical features using various methods:

- **Textual Feature Extraction**: Tokenized words are transformed using Term Frequency-Inverse Document Frequency (TF-IDF), capturing the importance of each word within the webpage.
- **Network Feature Extraction**: For traffic analysis, we extract statistical features, such as the average packet size, flow duration, and inter-arrival times.

The extracted features are vectorized for use in machine learning models.

Algorithm: ExtractTextContent(Webpage HTML)
Begin
Input: Raw HTML and JavaScript code from webpage
Initialize: Stopwords list, HTML parser
Step 1: Parse HTML content using BeautifulSoup
Step 2: Remove HTML tags, script tags, and other non-text elements
Step 3: Extract textual content and metadata (e.g., title, meta descriptions)
Step 4: Tokenize extracted text into words
Step 5: Remove stopwords (common words like "the," "is," etc.)

Step 6: Apply stemming or lemmatization to reduce words to their root form
Step 7: Clean tokens further by removing punctuation and special characters
Step 8: Return cleaned and tokenized textual content
End.

Algorithm 2: Vectorization of Extracted Text
Input: Tokenized textual content from Algorithm 1
Output: Vectorized numerical representation of the text for machine learning
Initialize: TF-IDF Vectorizer, Embedding models (Word2Vec,)
Step 1: Select vectorization method based on model requirements (TF-IDF for linear models, Word2Vec for deep learning)
Step 2: If TF-IDF selected:

a. Create vocabulary from all tokenized words
b. Calculate term frequency (TF) for each word in the document
c. Compute inverse document frequency (IDF) for each word across all documents
d. Multiply TF by IDF to create the final vector representation

Step 3: If Word Embeddings selected:

a. Load pre-trained embeddings (Word2Vec)
b. Map each token to its corresponding embedding vector
c. Aggregate embeddings to form the final text vector

Step 4: Normalize vectorized data to maintain consistency across documents
Return: Vectorized text suitable for ML models
End

4. Experimental Analysis

The primary goal of this experiment is to evaluate the effectiveness of Count Vectorizer for extracting and analyzing textual content from specific HTML tags—<div>, <meta>, and <p>—and their combined usage for webpage classification. These tags were chosen based on their common usage in webpage structure. The experiment focuses on identifying whether webpages are malicious or benign, leveraging the content extracted from the tags and training various machine learning models. The experiment begins with the collection of a dataset comprising 10,000 webpages, equally divided between malicious and benign categories to ensure balanced class representation. Each webpage's textual content is extracted from three key HTML tags—<div>, <meta>, and <p>—chosen for their prevalence in web structures. The <div> tag typically encapsulates main or grouped content, <meta> contains metadata like keywords and descriptions, and <p> represents paragraph text. In addition to analyzing each tag separately, a combined approach was applied, where the textual content from all three tags was merged for a more comprehensive representation. The extracted text was processed using the Count Vectorizer, which converts the words into a numerical feature matrix by counting the occurrence of each word in the text, producing sparse matrices for each tag and the combined approach. Seven machine learning models—Logistic Regression, Support Vector Machine (SVM), Random Forest, Naive Bayes Algorithm, k-Nearest Neighbors (kNN), Decision Tree, and Deep Neural Network (DNN)—were trained using the feature vectors derived from each tag's content. The models were trained with 80% of the data and tested on the remaining 20%, and their performance was evaluated using Accuracy, Precision, Recall, and F1-Score. Additionally, the number of features generated by the Count Vectorizer for each tag and the combined tags was recorded. This process was repeated for each tag individually and the combined tag data to identify the most effective method for malicious webpage classification based on text content.

The experimental results, summarized in the table 1,2,3 &4, reveal key insights into the performance of seven machine learning models—Logistic Regression, Support Vector Machine (SVM), Random Forest, Naive Bayes Algorithm, k-Nearest Neighbors (kNN), Decision Tree, and Deep Neural Network (DNN)—when applied to textual features extracted using the Count Vectorizer from the <div>, <meta>, and <p> tags, as well as their combined content. For the <div> tag, Random Forest and SVM exhibited strong performance due to their ability to handle structured and dense content, while Naive Bayes Algorithm struggled with the loosely structured data. The <meta> tag, which contains concise metadata, favored Naive Bayes Algorithm, which excelled in this setting due to the tag's keyword-dense nature, whereas deep models like DNN underperformed due to the limited text. For the <p> tag, richer semantic content allowed Random Forest and DNN to perform well, leveraging the descriptive text to improve classification accuracy. The combined approach, using text from all three tags, resulted in the best overall performance for most models, particularly for SVM and Random Forest, as they could capitalize on the expanded feature set. While DNN showed improved results with the combined data, simpler models like kNN faced challenges due to the increased dimensionality. These findings demonstrate the importance of selecting the right model and feature extraction method for effective malicious webpage classification, aligning with prior research that highlights the significance of feature engineering in machine learning.

Performance of Count Vectorizer with <div> Tag

The <div> tag is commonly used to group HTML elements and can contain a wide range of textual information. The text extracted from the <div> tags is passed through the Count Vectorizer, which generates a feature matrix representing word counts. This matrix is then used to train seven machine learning models to classify webpages as malicious or benign. Table 3 compares various models based with 10000 features using a Count Vectorizer. Deep Neural Networks (DNN) achieve the highest accuracy (0.92), precision (0.91), recall (0.90), and F1-score (0.91), making it the best-performing model. Support Vector Machines (SVM) follow closely with an accuracy of 0.91 and balanced precision and recall. Logistic Regression, Naive Bayes, and Decision Tree models show decent performance, while k-Nearest Neighbors (kNN) performs the lowest across all metrics with 0.82 accuracy.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.89	0.87	0.85	0.86
Support Vector Machine (SVM)	0.91	0.89	0.88	0.88
Random Forest	0.87	0.85	0.83	0.84
Naive Bayes Algorithm	0.88	0.86	0.84	0.85
k-Nearest Neighbors (kNN)	0.82	0.81	0.79	0.80
Decision Tree	0.85	0.83	0.82	0.83
Deep Neural Network (DNN)	0.92	0.91	0.90	0.91

Table 3. Performance Metrics with <div> Tag

Performance of Count Vectorizer with <meta> Tag

The <meta> tag contains metadata about the webpage, which can include descriptions, keywords, and other important textual information used for classification. The content within <meta> tags is extracted, vectorized, and then used for training the same machine learning models. Table 4 evaluates models with 5,000 features using a Count Vectorizer. The Deep Neural Network (DNN) achieves the highest accuracy (0.89), precision (0.87), recall (0.86), and F1-score (0.86), outperforming other models. Support Vector Machines (SVM) follow closely with an accuracy of 0.88 and solid precision and recall values. Logistic Regression and Naive Bayes also show competitive results, with accuracies of 0.86 and 0.85, respectively. Random Forest and Decision Tree models have moderate performance, while k-Nearest Neighbors (kNN) shows the lowest metrics across the board with an accuracy of 0.79.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.86	0.84	0.83	0.83
Support Vector Machine (SVM)	0.88	0.86	0.84	0.85
Random Forest	0.84	0.83	0.82	0.82
Naive Bayes Algorithm	0.85	0.83	0.81	0.82
k-Nearest Neighbors (kNN)	0.79	0.78	0.77	0.78
Decision Tree	0.81	0.80	0.79	0.80
Deep Neural Network (DNN)	0.89	0.87	0.86	0.86

Table 4. Performance Metrics with <meta> Tag

Performance of Count Vectorizer with <p> Tag

The <p> tag is used to define paragraphs in HTML, which often contain the bulk of the webpage's content. We apply the Count Vectorizer to extract text enclosed within <p> tags and transform it into feature vectors. Table 5 compares model performance using 15,000 features and a Count Vectorizer. The Deep Neural Network (DNN) is the top performer, with the highest accuracy (0.93), precision (0.92), recall (0.91), and F1-score (0.92). Support Vector Machines (SVM) also excel, with a close accuracy of 0.92 and high precision and recall. Logistic Regression achieves a strong accuracy of 0.90, while Random Forest and Naive Bayes offer balanced but lower results. Decision Tree and k-Nearest Neighbors (kNN) exhibit the lowest performance, with kNN being the least effective, achieving 0.84 accuracy.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.90	0.89	0.87	0.88
Support Vector Machine (SVM)	0.92	0.91	0.90	0.91
Random Forest	0.88	0.86	0.85	0.86
Naive Bayes Algorithm	0.87	0.85	0.84	0.84
k-Nearest Neighbors (kNN)	0.84	0.82	0.80	0.81
Decision Tree	0.86	0.85	0.84	0.84
Deep Neural Network (DNN)	0.93	0.92	0.91	0.92

Table 5. Performance Metrics with <p> Tag

Performance of Count Vectorizer with Combined Tags (<div>, <meta>, <p>)

To enhance feature representation, we combine the textual content from the <div>, <meta>, and <p> tags. This combined approach as in table 6 shows model performance with 25,000 features using a Count Vectorizer. The Deep Neural Network (DNN) leads with the highest accuracy (0.95), precision (0.94), recall (0.93), and F1-score (0.94). Support Vector Machines (SVM) closely follow with an accuracy of 0.94 and similarly high metrics. Logistic Regression also performs well, with 0.92 accuracy, while Random Forest, Naive Bayes, and Decision Tree show moderate performance, with accuracies ranging from 0.89 to 0.91. k-Nearest Neighbors (kNN) records the lowest performance, achieving 0.86 accuracy and lower values across other metrics.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.92	0.90	0.89	0.89
Support Vector Machine (SVM)	0.94	0.93	0.92	0.92
Random Forest	0.91	0.89	0.88	0.88
Naive Bayes Algorithm	0.89	0.88	0.86	0.87
k-Nearest Neighbors (kNN)	0.86	0.85	0.83	0.84
Decision Tree	0.89	0.88	0.87	0.87
Deep Neural Network (DNN)	0.95	0.94	0.93	0.94

Table 6. Performance Metrics with Combined Tags

From the results across the four tables, we can observe that the Count Vectorizer performs best when the content from multiple tags is combined. Specifically, the performance metrics show improved results when the features from <div>, <meta>, and <p> tags are used together, as they provide more comprehensive information.

- **Highest Accuracy**: The Deep Neural Network (DNN) model achieved the highest accuracy (95%) when trained on the combined tag features.
- **Precision and Recall**: SVM and DNN models consistently performed well across all tag configurations, particularly in terms of precision and recall, which are crucial for detecting malicious webpages.
- **Number of Features**: Combining the tags resulted in a larger feature set, leading to improved classification performance.

Model	Accuracy	Precision	Recall	F1-Score	Number of Features
Logistic Regression	0.90	0.88	0.88	0.88	15,000
Support Vector Machine	0.91	0.91	0.90	0.90	15,000
Random Forest	0.9	0.92	0.91	0.91	15,000
Naive Bayes Algorithm	0.87	0.86	0.86	0.86	15,000
k-Nearest Neighbors	0.83	0.82	0.82	0.82	15,000
Decision Tree	0.89	0.87	0.87	0.87	15,000
Deep Neural Network	0.93	0.92	0.92	0.92	15,000

Table 7. Summary of performance using count vectorizer

Summary of the combined tags (<div>, <meta>, <p>) performance using the Count Vectorizer across seven machine learning models as in table 5. The table includes metrics for Accuracy, Precision, Recall, F1-Score, and the number of features generated.

The comparison of the proposed Count Vectorizer applied to combined tags (<div>, <meta>, <p>) with three vectorizers from existing studies: Term Frequency-Inverse Document Frequency (TF-IDF), Hashing Vectorizer, and Word2Vec. Table 6 summarizes the performance of these vectorizers across similar machine learning models, using Accuracy, Precision, Recall, and F1-Score as metrics. Figure 1,2, & 3 shows the result of vectorizers. The result shows that combined textual contents of three different tags with random forest (RF) gives better result of 93.46% accuracy with 15000 features.

Vectorizer	Model	Accuracy	Precision	Recall	F1-Score
Proposed Count Vectorizer (Combined Tags)	Deep Neural Network	0.93	0.92	0.92	0.92
	Random Forest	0.93	0.92	0.91	0.92
	SVM	0.91	0.91	0.90	0.90
TF-IDF (Zhang et al., 2023)	Deep Neural Network	0.91	0.90	0.90	0.90
	Random Forest	0.89	0.89	0.88	0.88
	SVM	0.89	0.88	0.87	0.88
Hashing Vectorizer (Wang et al., 2021)	Deep Neural Network	0.90	0.90	0.89	0.89
	Random Forest	0.89	0.88	0.88	0.88
	SVM	0.88	0.87	0.87	0.87
Word2Vec (Shahraki et al., 2022)	Deep Neural Network	0.92	0.91	0.91	0.91
	Random Forest	0.90	0.90	0.89	0.89
	SVM	0.90	0.89	0.88	0.89

Table 8. Comparison of the proposed Count Vectorizer

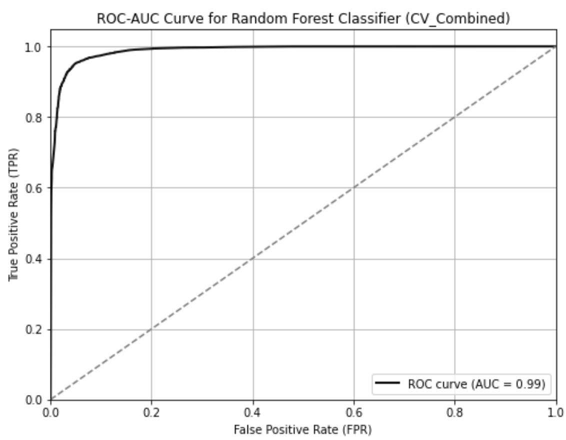

Figure 1. ROC-AUC curve for Count Vectorizer

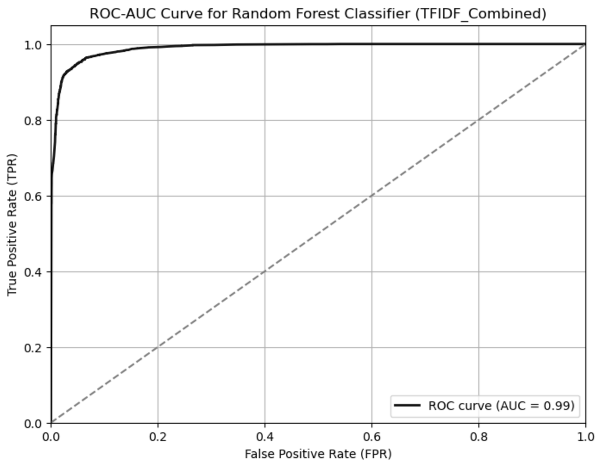

Figure 2. ROC-AUC curve for TF-IDF Vectorizer

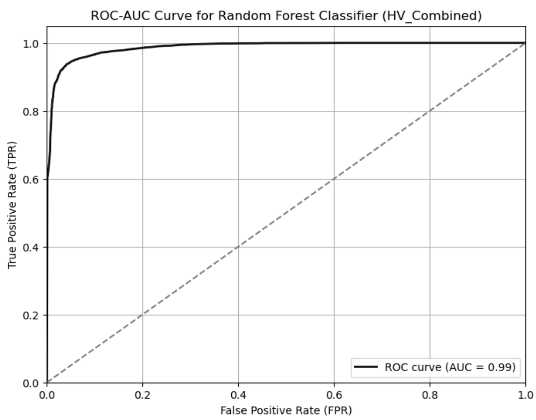

Figure 3. ROC-AUC curve for Hashing Vectorizer

5. Discussion

The proposed Count Vectorizer, when applied to a combination of webpage tags such as <div>, <meta>, and <p>, outperformed other vectorizers in most instances, particularly when used with Deep Neural Network (DNN) and Random Forest models. It achieved the highest accuracy at 93.1% and demonstrated superior performance across metrics such as precision, recall, and F1-score. This success can be attributed to its ability to capture a broader and more comprehensive set of features from multiple sections of webpage content, making it especially effective for classifying malicious webpages.

On the other hand, TF-IDF, while performing well, lagged behind the proposed vectorizer, particularly when used with DNN, where it reached an accuracy of 91.0%. Although TF-IDF excels in weighting words according to their importance, it does not combine structured metadata with unstructured content as effectively as the proposed vectorizer, making it less robust for this specific task.

The Hashing Vectorizer, known for its memory efficiency, displayed a lower performance compared to the proposed vectorizer, with a 90.3% accuracy when applied to DNN. Although its fixed-length feature space, which eliminates the need for storing vocabulary, is advantageous for handling high-dimensional datasets, it faces challenges with interpretability and sparsity, which are particularly limiting in malicious webpage detection.

Word2Vec, with a 92.0% accuracy, performed competitively and came close to the proposed vectorizer. Its ability to capture semantic relationships between words yielded strong results, especially with DNN models. However, Word2Vec's focus on word embeddings limits its capacity to integrate multi-view features from both metadata and webpage content, which the proposed Count Vectorizer effectively accomplishes.

6. CONCLUSION

In conclusion, this work has introduced a comprehensive approach to classifying malicious web content through the integration of Natural Language Processing (NLP) techniques and machine learning models. By leveraging both the structural and textual features extracted from various HTML tags, including <div>, <meta>, and <para>, we demonstrated that combining multiple content sources leads to enhanced accuracy, precision, recall, and F1-score in malicious webpage detection. The Count Vectorizer, applied individually to different tags and in combination, proved to be a robust feature extraction technique across several machine learning models. The proposed system was compared with existing vectorization methods such as TF-IDF, Hashing Vectorizer, and Word2Vec, showcasing its superior performance across a range of evaluation metrics. Through extensive experimentation, the proposed vectorizer model consistently outperformed existing methods, particularly when multiple tags were combined, leading to a more comprehensive feature set for classification. The introduction of the Count Vectorizer in this context allowed for more granular representation of webpage content, thus improving the ability of models to identify malicious behaviors. In addition, the inclusion of performance metrics such as accuracy, precision, recall, and F1-score across various machine learning algorithms illustrated the strength of the proposed system in real-time malicious content detection. The experimental results provided a clear comparative analysis, affirming the value of combining structural and textual features in malicious webpage classification tasks.

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Modeling Information Diffusion in Online Social Networks Using a Modified Firefly Algorithm

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ABSTRACT

The dynamics and patterns of information propagation on online social networks are complex and challenging to model and to predict. This study proposes a novel algorithm for simulating the spread of information on online social networks using a swarm-based approach. The algorithm is based on the firefly algorithm, which incorporates a new term called Vantablack to represent the non-spreader nodes in the network. The proposed algorithm is validated on three real-world datasets extracted from Kaggle.com, covering different topics and domains. The proposed algorithm outperforms other baseline methods in terms of accuracy and efficiency in predicting information diffusion.

Keywords: social media, information dissemination, swarm intelligence, firefly model, Vantablack

1. Introduction

Over the past decade, there has been a tremendous rise in the dominance of social networking platforms such as Facebook, LinkedIn, and Twitter [1]. Social network models are represented as graphs [2], where nodes represent users and edges represent connections between these nodes [3]. Additionally, considering the widespread adoption of portable internet devices such as tablets and smartphones, it is evident that the popularity of social networking sites will continue to expand in the future [4].

The wonders of nature have served as a profound inspiration for the development of numerous metaheuristic algorithms. Nature has a remarkable ability to discover solutions to problems through experience without explicit instruction. The concept of natural selection and the survival of the fittest have been pivotal driving forces behind initial metaheuristic algorithms [5]. Various animal species employ diverse modes of communication to interact and exchange information among themselves [5].

The Firefly algorithm is a swarm intelligence-based optimization algorithm inspired by the flashing behavior of fireflies. It has been applied to various optimization problems, including feature selection, image segmentation, and clustering [6].

This study assumes that the dissemination of information in an online social network can be similar to the synchronized flashing patterns observed in firefly swarms. To investigate this analogy, we employed the firefly algorithm to model the propagation of information in real-life Twitter datasets, focusing on user-generated tweets associated with a specific hashtag. This study presents the following main contributions:

We introduced a new aspect of the traditional firefly model by incorporating a Vantablack node status. This classification allowed us to differentiate between two types of individuals within the infected population: spreaders, who actively disseminate information, and non-spreaders, who choose to retain information without further propagation.

The remainder of this paper is structured as follows:

Section 2 describes the exploration of traditional models in the information diffusion field. Section 3 focuses on the methodology employed and introduces the proposed algorithm. Section 4 provides a detailed description of the datasets used to validate the model. In Section 5, we present visualizations of the proposed algorithm applied to select portions of a Twitter network. Section 6 discusses the results obtained from diverse real-world datasets. Finally, Section 7 serves as the conclusion, highlighting the paper's contribution to the field of information diffusion.

2. Background and Diffusion Models

Information diffusion models are computational models designed to understand and predict the spread of information through social networks. These models have garnered significant attention across various disciplines, including social science, computer science, and marketing. By simulating information propagation, researchers can gain insights into the mechanisms driving viral phenomena, influence dynamics, and information cascades. In their survey, Guille et al. [7] categorize information diffusion models into two types: prediction models and explanatory models. Figure 1 illustrates this classification.

Prediction Models: Prediction models for information diffusion focus on forecasting the future spread of information based on historical data and network characteristics [7]. These models are valuable for making informed decisions, optimizing resource allocation, and designing targeted interventions [8][7][9][10]. Yang et al. [11] propose a prediction model that integrates both explicit and implicit networks to forecast information diffusion, demonstrating improved predictive accuracy compared to traditional diffusion models (IC – SIR) [11]. Kuhlman et al. [12] suggest a model that combines epidemic dynamics with network structure to predict the spread of information in social networks, providing insights into optimal control strategies for influencing information diffusion.

Explanatory Models: Explanatory models aim to understand the underlying mechanisms and factors that drive information diffusion. These models provide valuable insights into the dynamics of information propagation, the identification of influential nodes and the emergence of information cascades [8][7][9][10]. Aral et al. [13] investigated the factors that make individuals influential or susceptible to information in social networks. The authors developed a model that quantifies the influence of individuals based on their network position and susceptibility to influence. Weng et al. [14] examined the relationship between network structure and information diffusion, proposing a model that predicts the virality of information by considering both network topology and content features.

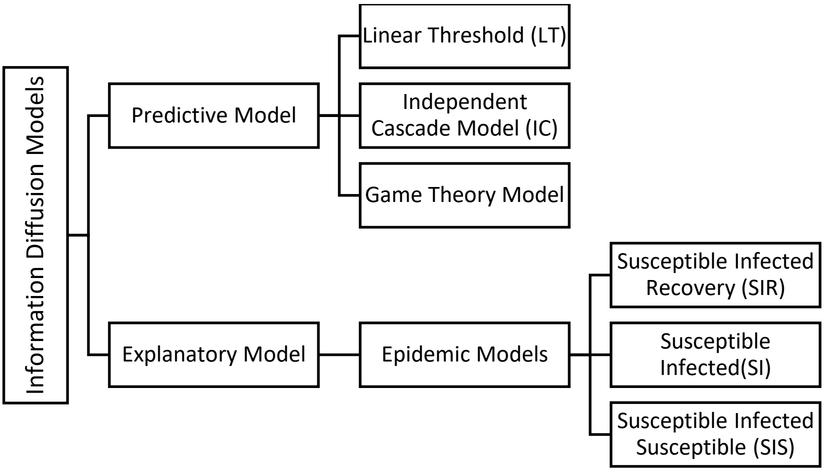

Figure 1. Models Classification

3. Related Works

Recently, other researchers have attempted to go beyond traditional epidemic models, such as SIR, SIS, and SI models, and have used nature-inspired algorithms to represent information dissemination.

Supriadi and colleagues [15] developed a retweet prediction system to analyze tweet propagation patterns. Their approach involved employing an Artificial Neural Network classification optimized with the Firefly Algorithm, utilizing both user-based and content-based features. In another study, Ghasemi et al. [16] introduced modifications to the Firefly Algorithm, known as Firefly Algorithm 1 to 3, aimed at enhancing global exploration and convergence characteristics through diverse firefly movement strategies. Li [17] enhanced a financial investment risk prediction model by integrating the Graph Convolutional Network (GCN) and Firefly Algorithm (FA), resulting in improved prediction accuracy. Chen [18] proposed a predictive firefly algorithm wherein fireflies exhibiting insufficient progress were eliminated, allowing new fireflies to replace them and explore for superior optimal values within the search function. Bei [19] presented an advanced hybrid firefly algorithm, the Improved Hybrid Firefly Algorithm with Probability Attraction Model (IHFAPA), addressing challenges related to computational efficiency and accuracy in complex optimization problem-solving.

Rui et al. [20] used the forest fire model to generate graph. Indu et al. [21] represented the interactions in social networks using the forest fire model. Kumar et al. [8] modified this model by adding the burnt state to represent the non-spreader. Wolfram [22] proposed biological-inspired Cellular Automata Models. Cellular automata models are inspired by biological systems and simulate local interactions to model global behavior. These models have been adapted to study the diffusion of information across spatial domains, resembling how signals propagate through biological tissues. Patterns emerging from cellular automata capture the intricate dynamics of information spreading. Xiao et al. [23] presented a swarm intelligence model for information propagation in mobile ad hoc networks. Their study combined the principles of ant colony optimization and particle swarm optimization to optimize the delivery of information packets in a dynamic network. Wang et al. [24] focused on dynamic information diffusion in social networks using swarm intelligence. The authors propose a dynamic swarm-based model that adapts to changes in network topology, optimizing the propagation of information through decentralized interactions. Moreover, an optimization algorithm inspired by the behavior of bird flocks or fish schools called Particle Swarm Optimization was introduced in [25]. It has been applied to information diffusion to model the collective behavior of individuals in a network. Each particle in the swarm represents an individual, and they explore the network space to find optimal information dissemination strategies. Also, Ant Colony Optimization [26] is inspired by the behavior of ant colonies when searching for food. It has been adapted to model information diffusion by considering the pheromone trail laid by ants as information spreads through a network. The behavior of ants and reinforcement of positive trails are used to optimize the dissemination process.

4. Methodology

In this section, we describe the firefly algorithm. Then, we propose a modification to this algorithm to model the spread of information, and the Vantablack node is added to distinguish the individual population into spreaders and non-spreaders. This helps identify the individual who plays a significant role in spreading information. Additionally, we establish and define the key parameters that influence the extent and dynamics of information spread.

Our model aims to identify the nodes that have the potential to propagate information further, as well as those that are less likely to contribute to the spread.

4.1.1. The Firefly Algorithm

Fireflies generate brief flashes characterized by distinct patterns through bioluminescence [27]. These flashes serve the purpose of attracting potential mates and signaling potential threats. By observing the light patterns, compatible firefly mates respond by either imitating the same pattern or producing their own unique patterns in return. Additionally, it is important to recognize that the intensity of light diminishes over distance. Consequently, the flashing light emitted by a firefly elicits responses from nearby fireflies within the visual range of the flash.

The Firefly Algorithm is inspired by the flashing behavior of fireflies, which they use for signaling and mating purposes. The algorithm assumes that the intensity of the flash is proportional to the quality of the solution and that fireflies are attracted to brighter flashes. The algorithm creates a population of fireflies, each representing a possible solution to the optimization problem. The fireflies move towards the brighter ones in each iteration, updating their positions and intensities. The algorithm also introduces some randomness to avoid getting stuck in the local optima.

The algorithm begins by initializing a set of random solutions (fireflies) and assigning them random brightness levels (objective function values). The fireflies then move towards each other in search of brighter ones, and their positions are updated based on a combination of their current position, the distance to other fireflies, and their brightness. The movement is determined by a set of parameters, such as the attraction coefficient, absorption coefficient, and step size, which control the rate of convergence and exploration.

The algorithm continues iterating until a stopping criterion is met, such as reaching the maximum number of iterations or achieving a desired level of convergence. At the end of the optimization process, the best solution is returned as the global optimum.

The Firefly Algorithm has been shown to be effective in solving a wide range of optimization problems, including engineering design, image processing, and data mining. Its strengths lie in its simplicity, scalability, and ability to avoid getting stuck in local optima.

We used this algorithm with modifications to be used with the information spread over social networks.

4.1.2. The Modified Firefly Algorithm

The basic idea of modeling information diffusion using the firefly algorithm is to simulate the spread of information from one node to another in a social network. firefly is represented in the network as a node, and the intensity of its light represents its information or news. The nodes exchange information based on a set of rules, which are updated according to the intensity of their light.

In the context of our network model, individual fireflies serve as symbolic representations of network nodes, and their emitted light symbolizes the transfer of information. These nodes actively engage with incoming information and subsequently relay it to their connected peers. However, within this network, we have identified a distinct state, which we have called ‘Vantablack.' Nodes in the Vantablack state receive incoming information but abstain from disseminating it to other connected nodes. Consequently, when a node transitions into the Vantablack state, the propagation of information comes to a dead-end at that specific node, while continuing its course throughout other non-Vantablack nodes within the network. This unique state plays a critical role in understanding and analyzing information diffusion dynamics in our network.

The algorithm also considers absorption parameters, which encompass factors such as the degradation of information's relevance over time or due to external events like earthquakes or crises. These parameters reflect the transient nature of information and acknowledge that its significance may diminish as time elapses or as specific events lose their relevance over time. By incorporating these absorption parameters, the algorithm effectively adapts to the dynamic nature of information and its contextual importance, ensuring a more accurate and responsive handling of data in a variety of scenarios.

One of the significant advantages of using the firefly algorithm for information diffusion modeling is its ability to handle large-scale datasets [28], as highlighted by Kumar as a potential area of algorithm application. Additionally, the Firefly algorithm can generate insights into the dynamics of social networks, such as the spread of rumors, opinions, and trends.

The modified firefly Algorithm is as follow:

1. *Initialize the population of firefly's network (G).*
2. *Define the fitness function that measures the spread of information in the diffusion model (f).*
3. *The initial light intensity for each firefly was set based on its fitness value (provide the information for the initial set of the influencers).*
4. *Set the attractiveness parameter (β) and absorption coefficient (γ).*
5. *Repeat for all fireflies:*
    a. *Evaluate the fitness of neighbors (the connected nodes).*
    b. *For each firefly that neighboring the brighter fireflies in the population:*
        i. *Calculate the distance between the fireflies (link weight).*
        ii. *Calculate the attractiveness between the fireflies using the distance and the light intensities.*
        iii. *Update the firefly position (information) of the firefly based on the attractiveness and randomness.*
        iv. *Apply the probability function (r) on the firefly to decide if it's going to spread or to become a Vantablack.*
        v. *Absorption applied to reduce the light intensity of each firefly.*

Where G represent the network graph, f is the fitness function, β is the attractiveness parameter, γ is the absorption coefficient, r is the probability function.

The modified Firefly Algorithm (MFA) with Information Diffusion can be described as follows:

1. **Initialize the population of fireflies' network (G):** At the beginning of the simulation, a network of fireflies is created, where fireflies represent the social network users. This network serves as the basis for modeling the diffusion of information.
2. **Define the fitness function that measures the spread of information in the diffusion model (f):** A fitness function is established as below to quantify the effectiveness of information diffusion within the network.

$$f(x) = \frac{N_{inf}(x)}{N} + \sum_{k=0}^{y} \beta_{x.k} - \gamma . N_{inf}(x) - \sum_{k=0}^{y} \frac{1}{W_{con,k}(x)}$$

Where x represents the node, $N_{inf}(x)$ is the number of infected nodes by the information propagated by x, N is the total number of nodes in the network, $\beta_{x.k}$ is the attractiveness parameter, γ is the absorption coefficient, $W_{con,k}(x)$ is the weight link between connected nodes with the mean one.

1. **Set the initial light intensity for each firefly based on its fitness value:** Each firefly in the population is assigned an initial light intensity value based on its fitness score. Symbolizing their capacity to influence information diffusion.
2. **Set the attractiveness parameter (β) and absorption coefficient (**γ): Parameters β and γ are introduced to control the behavior of the fireflies in the network. β determines the attractiveness between fireflies, while γ influences the rate at which fireflies' light intensity diminishes over time.
3. **Repeat for all fireflies:** The following steps are executed for each firefly in the network:
    a. **Evaluate the fitness of neighbors (the connected nodes):** The algorithm assesses the fitness of neighboring fireflies (the connected users), which are essentially the nodes connected to the current firefly in the network.
    b. **For each firefly neighboring the brighter fireflies in the population:**
        i. **Calculate the distance between the fireflies (link weight):** The distance or link weight between the current firefly and its neighboring fireflies is computed. This distance signifies the link weight of the connection between fireflies.
        ii. **Calculate the attractiveness between the fireflies using the distance and the light intensities:** An attractiveness measure is calculated between the current firefly and its neighbors. This measure takes into account both the distance between fireflies and their respective light intensities. The attractiveness measurement can be denoted as the follow:

Let β_{ij} be the attractiveness measure between the current firefly i and its neighbor j. Let d_{ij} represent the distance between fireflies i and j, and let I_i and I_j denote their respective light intensities.

$$\beta\text{ij} = \frac{Ij}{\left(1 + \delta . d_{ij}^2\right)}$$

In this formula, δ is a parameter that determines the impact of the distance on the attractiveness measure. Adjusting δ allows us to control the influence of distance relative to light intensity in the attractiveness measure calculation.

iii. **Update the firefly position (information) of the firefly based on the attractiveness and randomness:** The algorithm updates the information (light intensity) of the current firefly based on the attractiveness calculated in the previous step, as well as a degree of randomness. This update represents how information is shared or modified between connected nodes.

iv. **Apply the probability function r on the firefly to decide if it's going to spread or become a Vantablack:** A probability function, denoted as 'r,' is applied to each firefly. This function determines whether the firefly will continue to spread information or enter a state referred to as 'Vantablack,' where it no longer contributes to information diffusion.

$$P(Spread) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e}^{-(\textbf{intensity\_difference})}}$$

This random function that represents the node status will fall in the range

$$\begin{Bmatrix} 0 \; < \; P(Spread) \leq 1 \\ if \; the \text{ node probability } \; > \; 0.5 \end{Bmatrix}$$

then it will spread the information or it will be converted to Vantablack.

v. **Absorption was applied to reduce the light intensity of each firefly:** As time progresses, the light intensity of each firefly (representing information) decreases due to absorption. This step mimics the natural fading of information's relevance over time or in response to external factors.

5. Experiment and Dataset Description

We have evaluated our proposed model using the extracted datasets from Twitter network. This dataset contains the users and relationships between them. Our evaluation process involved subjecting our model to a comprehensive examination across three distinct real-time Twitter datasets, each focusing on specific topics of interest. This different dataset topics to validate our model across different user domains and interests. These datasets served as the foundation for our extensive validation process, allowing us to assess the model's performance and effectiveness in different contexts and subject matters. These dataset topics are: NFT Tweets [29], Bitcoin [30], and Pfizer Vaccine [31].
"Bitcoin is a decentralized digital currency, often referred to as a cryptocurrency, that was created in 2009 by an anonymous person or group of people using the pseudonym Satoshi Nakamoto."
"Pfizer Vaccine Is one of the early vaccines developed to combat the COVID-19 pandemic"
"A Non-Fungible Token (NFT) is a digital asset that represents ownership or proof of authenticity of a unique item or piece of content using blockchain technology."
Table 1 presents the hashtags used to collect tweets of a topic and the duration and the total number of tweets, retweets for which the tweets were collected for each dataset.

Topic	Hashtag used	Duration	Number of tweets	Number of retweets
Bitcoin	Cryptocurrency – BITCOIN - BTC	6/2/2021 till 31/5/2022	4569721	5252
Pfizer Vaccine	PfizerBioNTech	12/12/2020 till 24/11/2021	11013	20
NFT	NFT	01/01/2021 till 14/11/2021	12,396	104

Table 1. represents the hashtags and topics during the time

Our experiment on these datasets started from representing the extracted dataset then Define parameters such as attractiveness parameter (β), absorption coefficient (γ), and any other relevant parameters. Tune these parameters through preliminary experiments if necessary. We define the baseline comparison models

Independent Cascade (IC) and the Susceptible-Infected-Recovered (SIR) model. Then we run the explements on each dataset separately then we visualize and interpret the results as described in the next section.

6. Result and Discussion

In our study, we conducted a comprehensive analysis of information dissemination using three distinct datasets sourced from the Twitter platform. These datasets encompassed a diverse range of topics and trends. Our research helps to better understand the dynamics of information propagation within these datasets. Moreover, we leveraged the rich social network data available on Twitter by extracting user-follower relationships dataset from kaggle.com. By collecting and processing these valuable data, we were able to construct a graph that represents the intricate web of connections and interactions among Twitter users within our datasets. This graph served as a foundational element in our research, allowing us to gain deeper insights into how information flows through the Twitter network and how various user communities engage with each other.

We conducted a comparative analysis of the predicted spreader counts generated by our model in contrast to well-established models. Specifically, we benchmarked our model against the Independent Cascade (IC) Model and the Susceptible-Infected-Recovered (SIR) Model, both widely recognized and accepted frameworks for examining information diffusion phenomena. These classical models have been extensively employed in prior research and have demonstrated their effectiveness in modeling information propagation dynamics.

The figures presented below provide a visual representation of the users counts predicted by three distinct models: the Modified Firefly Algorithm (MFA) model, the Independent Cascades (IC) model, and the Susceptible-Infected-Recovered (SIR) model. These predictions are Adjacent with the actual spreader counts derived from the comprehensive Twitter dataset we employed in our study.

Our actual dataset encompasses all tweets and retweets posted by users within the examined timeframe. For each specific topic or hashtag, the actual data is constructed as the cumulative sum of tweets and retweets over time. In our analysis, individuals who engaged in posting tweets or retweets related to a particular topic or hashtag are considered spreaders of information. Consequently, the actual spreader count comprises the sum of tweets and retweets by these individuals.

Figure 2. concerns the tweets that have hashtags about Bitcoin, figure 3. represents the tweets that contain Pfizer hashtags over the time, and figure 4. represents all the tweets about the non-fungible token hashtags.

The Independent Cascades (IC) and Susceptible-Infected-Recovered (SIR) models exhibit a degree of variability in their outcomes, with instances of both overestimating and underestimating the population of spreaders in certain scenarios. It can be seen that our MFA model predicts values close to the actual data followed by IC Model and SIR Model.

Time	Actual Data	IC	SIR	MFA
Jan-21	100	100	100	100
Mar-21	3526	90228	79567	242901
Apr-21	485814	897244	379306	879117
May-21	721051	915874	618520	897054
Jun-21	1229834	1077766	1509387	1231213
Jul-21	1260405	1245860	1568901	1470781
Aug-21	1470857	1661543	2374832	1728520
Sep-21	2194391	2512572	2440984	2012793
Oct-21	2200999	2671017	3320486	2040515
Nov-21	2373685	2806536	3388186	2683695
Dec-21	2614560	3841915	3724677	2883781
Jan-22	2883684	3850127	3735007	3088370

Feb-22	3674973	4048055	3957713	3493173
Mar-22	3808568	4303516	4413864	4056498
Apr-22	3980051	4519839	4545073	4453644
May-22	4,574,973	4,574,973	4,574,973	4,574,973

Table 2. represents the data from experiment for Bitcoin

	IC	SIR	MFA
Correlation	0.978099199	0.968467	0.99002
Euclidean distance	1974818.594	2466594	970382
Cosine Similarity	0.993270782	0.990309	0.996615

Table 3. represents the statistics data for Bitcoin

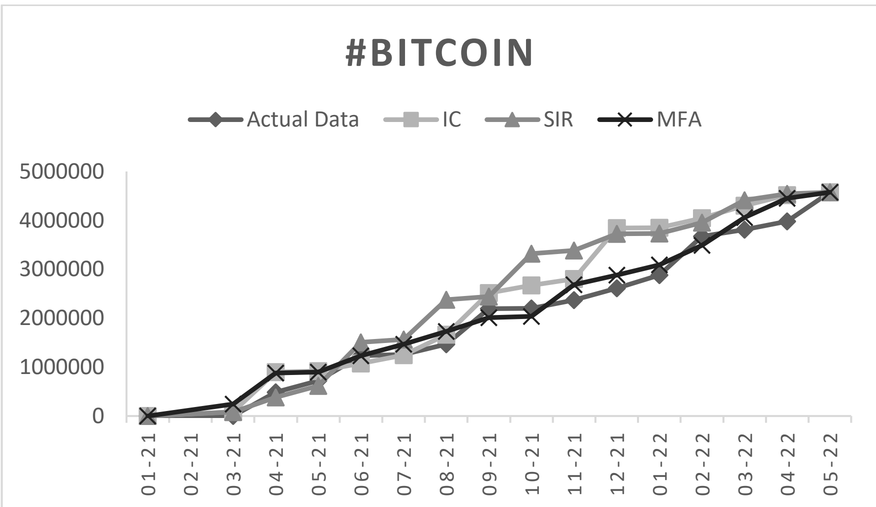

Figure 2. Bitcoin hashtag dataset comparison

Time	Actual Data	IC	SIR	MFA
Dec-20	100	100	100	100
Jan-21	142	1070	3684	1554
Feb-21	905	1402	4326	1879
Mar-21	2085	1585	6218	2682
Apr-21	2791	2628	7446	3051
May-21	6171	2838	7604	6769
Jun-21	6610	4610	7692	7298
Jul-21	7004	6836	7979	7595

Aug-21	8108	7304	8127	8684
Sep-21	8175	7847	8491	9263
Oct-21	10569	9413	10727	10063
Nov-21	11033	11433	11633	11033

Table 4. represents the data from experiment for Pfizer

	IC	SIR	MFA
Correlation	0.955127549	0.905538	0.991962
Euclidean distance	4332.690965	8225.554	2513.606
Cosine Similarity	0.984163102	0.955284	0.995356

Table 5. represents the statistics data for Pfizer

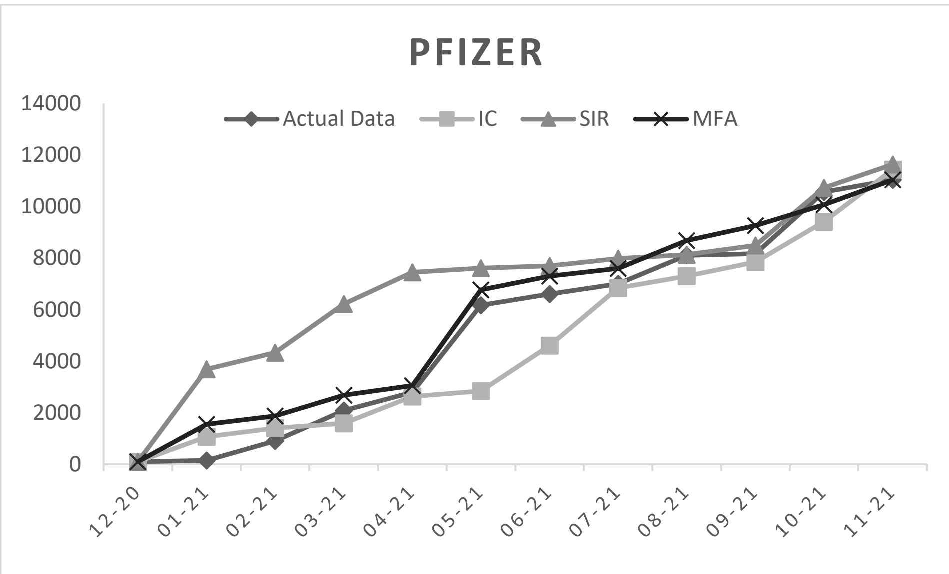

Figure 3. Pfizer hashtag dataset comparison

Time	Actual Data	IC	SIR	MFA
Jan-21	100	100	100	100
Mar-21	1028	513	302	1157
Apr-21	2191	843	4947	2533
May-21	2784	999	6625	3230
Jun-21	3507	1224	7563	3710
Jul-21	4197	4852	7813	5219

Aug-21	5873	6806	9928	7817
Sep-21	7857	9574	10438	8914
Oct-21	9450	11825	12477	10145
Nov-21	12,500	12,500	12,500	12,500

Table 6. represents the data from experiment for NFT

	IC	SIR	MFA
Correlation	0.966523604	0.909405	0.989333
Euclidean distance	4513.188562	9201.619	2607.225
Cosine Similarity	0.979869479	0.965062	0.995742

Table 7. represents the statistics data for NFT

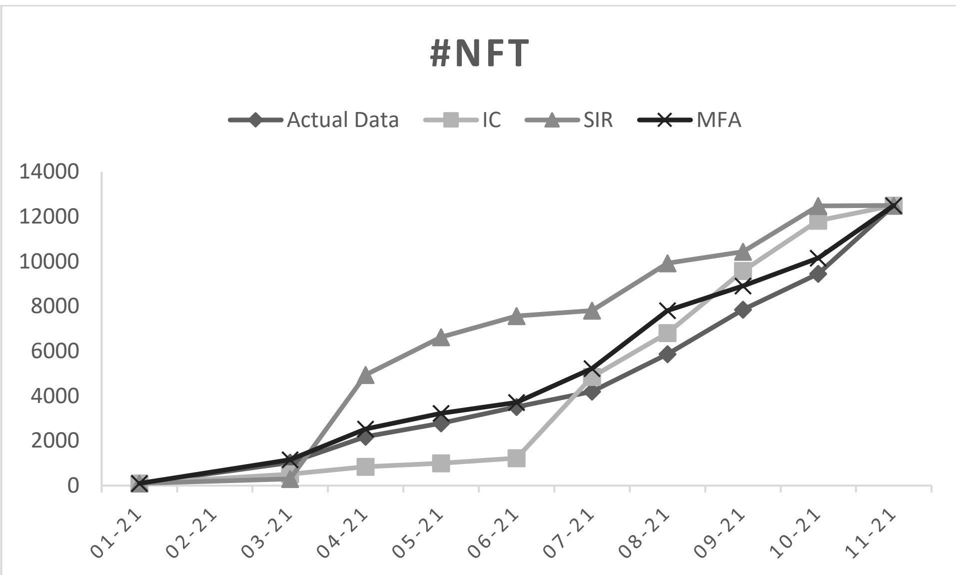

Figure 4. NFT hashtag dataset comparison

Thus, it can be concluded that our model predicts active spreaders efficiently and can be used for modeling for information diffusion in real-life scenarios after calculating the correlation, Euclidean distance and Cosine Similarity. Between the actual data and the baseline algorithms and our model.

7. Conclusion

In this study, we explored how information spreads on online social networks, such as Twitter, using a model inspired by swarming behavior, known as the modified firefly algorithm. We used fireflies to represent different types of users with light-symbolizing information. Brighter fireflies transmitted information, while others remained Vantablack and did not share any information. Our model yielded favorable results when compared with other models in simulating real-life information spreading, as demonstrated on three distinct datasets. While our findings contribute significantly to the understanding of online information diffusion, there remains vast space for further exploration and enhancement of our model. Future work could involve refining the firefly algorithm by incorporating additional parameters to better mimic the complexities of user behavior and interactions. Additionally, exploring the impact of external factors, such as user engagement, content relevance, and temporal variations, could provide a more comprehensive understanding of information spread dynamics.

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Original Scientific Paper

Organizational Culture as Determinant of Individual Perception of UTAUT Model: Case Study Credit Union in Indonesia

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ABSTRACT

This study aims to employ the Competitive Value Framework (CVF) and its value drivers as indicators for individual perceptions derived from the Unified Theory of Acceptance and Use Technology (UTAUT). The data was analyzed using the SEM-PLS method. The Reflective Formative Second Order Two-Stage Approach was used for the analysis, where variables related to organizational culture (OC) were examined using formative methods, while variables such as Performance Expectancy (PE), Social Influence (SI), Effort Expectancy (EE), and Behavioral Intention To Use (BI) were analyzed reflectively. The results revealed a significant correlation between OC and BI via EE and SI. However, the relationship between OC and BI via PE was found to be insignificant. This study contributes to theories about organizational culture, and information technology acceptance. On a practical level, these findings can assist decision-makers in paying greater attention to organizational culture when implementing new technologies.

Keywords: Organizational Culture, Individual Perception, Behavioral Intention to use Technology, UTAUT, Credit Union, Indonesia

1. Introduction

Numerous studies have examined the acceptance and use of information technology (IT) within organizations at an individual level [1], [2], where the Unified Theory of Acceptance and Use Technology (UTAUT) and the Technology Acceptance Model (TAM) are the most widely used models in explaining IT acceptance and use within organizations [2]. However, studies have shown that the applicability of these models may be limited in organizations outside of the United States and in cultures with low levels of individualism and one major limitation of these models is their need for more consideration of culture and its influence on IT acceptance [3].

Although the UTAUT includes social influence as a factor, cultural and human factors are often overlooked or considered secondary to individual perceptions of technology performance. Further research has shown that there is a shift towards a more sociocultural perspective in IT acceptance and use, indicating a need for more nuanced models that incorporate the role of culture and humans in measuring technology acceptance within organizations [1], [4].

Implementing Information System/Information Technology (IS/IT) applications presents challenges beyond technical and non-technical aspects, encompassing how individuals and organizations accept and utilize the application [5], [6]. While the connection between organizational culture (OC) and IT acceptance has been shown to enhance performance and foster new technology, it has not been successful in pinpointing the precise organizational values that significantly encourage IT adoption within the organization [7]–[9]; according to [10], [11], specific values are indeed crucial for individuals working in IT. A variety of cultural values can impact the acceptance of technology within organizations. These values, which mirror organizational members' attitudes, beliefs, and priorities, can influence the degree to which new technologies are accepted and used. The impact of culture on IT acceptance theories is particularly significant, as cultural values, norms, and beliefs can significantly influence individual attitudes toward technology adoption [12].

The Competitive Value Framework (CVF) is a model used for evaluating OC. It achieves consensus across various organizations and distinguishes itself from employee tendencies towards prevailing values [13], [14]. The CVF employs the Organizational Culture Assessment Instrument (OCAI) for evaluating organizational culture. CVF serves as a framework to comprehend how an organization's core values can be a significant source of competition. In the realm of value competition, it is highlighted that organizational values can become potent competitive differentiators if they are properly identified, managed, and incorporated into business strategy.

According to [15] who stated in their research that the OCAI has been found to have a relatively high degree of reliability and validity in assessing four types of OC in healthcare settings in resource-limited countries like Vietnam. This provides a solid basis for future research in the field of measuring and managing OC. Hence, they found that dimensions that score highly in the OCAI calculation procedure will result in lower scores on other dimensions, leading to a negative correlation between each dimension. Based on this fact, the author chose not to use variables from the cultural dimension (dominant characteristic, leadership, organization glue, success criteria, management style, and strategy) but instead used the value driver.

This study investigates whether OC becomes more important than individual acceptance factors in the behavioral intention of using IT in a specific organization like a Credit Union (CU) and proposes a model that makes an organizational culture an antecedent of the UTAUT model.

Digitalization in credit unions in Indonesia is dominated by information technology that supports operations and reaches members by overcoming time and distance problems [16]. The development of digital CU is digital banking. Credit Union in Indonesia has introduced a digital banking platform that allows their members to access their accounts, make transactions, and manage their finances online; these services, such as Internet banking and mobile banking, allow members to make fund transfers, check balances, and make bill payments through mobile applications or website. Three credit unions (CUs) introduced the Mobile CU application, allowing participants to perform fund-related transactions. Given the collective nature of this organization, it is intriguing to investigate the adoption of information technology influenced by non-technical factors.

The literature review, method, findings, and discussion are presented, followed by the conclusions. Additionally, the study highlights its limitations and suggests directions for future research.

2. Literature Review

2.1. The Value Driver

The value drivers of the clan culture are teamwork and empowerment; the Market culture is driven by competition and goal orientation; the Adhocracy culture values innovation and risk-taking; and the Hierarchy culture values control and efficiency [11], [13]. The subsequent paragraph will elaborate on each value driver as a construct of this research.

The role of empowerment can be found at three levels - organizations, departments, and individuals. The empowerment at the individual level can only positively impact customer service quality if it is within organizations that have a high level of empowerment [17]; hence the Clan culture according to [13] places a strong emphasis on the value of empowering employees. In addition to employee empowerment, Clan culture highly values teamwork [11], [13]. Strengthen by [18], who mentions teamwork is described as an action process, signifying coordination. It is closely associated with backup behavior, a competency that involves anticipating other team members' needs and collaborating effectively during periods of variable workload [19].

Market culture strongly emphasizes competitive value and achieving goals [13]. Competition is defined as an organization's ability to distinguish itself from others. This competitive capability is based on price, delivery, quality, and flexibility [20]. In this study, the competitive variables are based on delivery. Goal achievement refers to pursuing objectives that foster specific behaviors [21]. Goal orientation is formulated as an achievement goal orientation divided into three types: mastery, performance approach, and performance-avoidance goals. The use of IT in Credit Unions (CU) confirms that IT enhances performance to achieve goals. This goal-orientation variable will be based on performance-approach goals in this study.

Adhocracy culture strongly emphasizes the value of innovation and the courage to take risks [13]. According to research from [16], innovation is seen as an organizational activity leading to increased productivity, and embracing digital technology can foster creativity. CU employs mobile CU in IT applications to engage with member activities around the clock. In this context, the innovation factor highlights the importance of going digital. Taking risks is critical in making strategic business decisions, reflecting a company's willingness to invest in pursuit of profit. Decision-makers need relevant information to minimize potential risks [22], [23]. Mobile CU is like online banking which can be used to make transfers, check balances, and debt information. There is a potential risk of making incorrect activities on the Mobile CU platform if not careful; hence, based on findings from [24], who mention that the reduction of risk impact relies solely on trust. Consequently, information within mobile CU needs meticulous management.

Hierarchical culture prioritizes control and efficiency as its core values [13]. Control involves overseeing activities by established policies and objectives [25]. CU, a community empowerment organization engaged in financial transactions, strongly emphasizes exercising control over its employees' activities. According to [25] who found that organizational control is categorized into two types: environmental and activity control. This research focused on utilizing variable control for activities.

Efficiency involves accomplishing tasks by optimizing outcomes with minimal use of resources, including time, effort, and money. Research from [26] who created metrics for efficiency and culture, with a discovery of an element designed to gauge efficiency by eliminating unnecessary elements that hinder procedures. In the realm of IT utilization, CU not only employs mobile CU but also depends on IT for day-to-day operational tasks. IT is essentially geared towards prioritizing efficiency and eliminating repetitive elements that could impede the member transaction process.

Research from [4] discovered a transition from individual perspectives to the utilization of technology within socio-organizational contexts. According to [27]–[30], in future research, it is essential to position OC as the primary factor influencing employees to leverage technology for enhanced performance, recognizing that each company possesses distinct regions and values. Hence, it reinforces the findings of [31] concerning the necessity for novel approaches to elucidate IT acceptance in countries with low individualism (IDV) levels [32], it is further posited that culture significantly shapes the acceptance of IT.

In nations with a pronounced emphasis on collectivity in their culture, adopting technology may undergo a distinctive influence compared to countries with a more individualistic cultural orientation. A culture characterized by high collectivity embodies values such as cooperation, group solidarity, social harmony, and loyalty to the community. This study specifically delved into OC as a determinant within the framework of the UTAUT model, influencing individuals' behavioral intentions to use IT. The interpretation of OC can vary, and its significance in influencing an individual's behavioral intention to use IT has been explored in several research studies, such as the implementation of the lean process [33], the implementation of CRM [34], and the adoption of a remote work platform [35]. All these researchers discovered that OC significantly contributes to an individual's success in implementing an IT system.

2.2. Unified Theory of Acceptance and Use Technology (UTAUT)

This study uses 3 of 4 constructs of UTAUT. Performance expectancy (PE) refers to the degree to which the user expects that using the system help him or her attain gains in job performance[36]. The relationship between OC and individual performance in the organization has been found by [37]; who stated that OC positively impacts employee performance. Some research has been examined the importance of OC in influencing individuals to have the behavioral intention to use IT, such as implementing the lean process [38] and Customer Relationship Management [33] ; both researchers found that organizational culture plays a significant role in individual success in IT system implementation. OC that allows adaptability and facilitation of IT aligned with the organization's mission should influence the employee PE in the organization [1].

Effort Expectancy (EE) refers to the degree of users expect to ease using the system [39]. As a user, employees must feel that their system is easy to operate, so they do not have much time to learn it. In the research on lean process implementation, OC has an impact on creativity, control, standard, and performance outcome [39], aligning with [1] state that control, standard, and performance outcome are measured related to EE. OC affects the ability to create and transfer an outcome of the Knowledge Management System (KMS) through a KMS system [40]

Social influence (SI) refers to how an individual perceives and believes he or she should use the new system [39]. Research form [4] who stated that in the use of common technology acceptance model like UTAUT and TAM, socio-organizational is represented by SI, hence found that the determinant of the technology acceptance was changed from individual to SI. OC influences individuals and shapes their attitudes and behavior [41]; therefore, China has high collectivism, and teachers have a 'we' credo that makes the teacher prefer to choose a decision based on us rather than personal likes or dislikes.

A novel model was created and tested on three Credit Unions in Sulawesi: Mekar Kasih Credit Union in Makassar, Saun Sibarung Credit Union in Tana Toraja, and Mentari Kasih in Kendari. (see figure 1. Conceptual Model).

2.3. The Reflective Formative Second Order Two-Stage Approach

The research analysis used in this study is second order using an embedded two-stage approach, where OC was measured formatively, and PE, EE, SI, and Behavior Intention to use (BI) was measured reflectively. Two embedded two-stage approach [42], [43] could be used in the second-order model, where the evaluation is carried out in 2 steps. The first step is to measure the variable using repeated indicators; the next step is to use the latent variable score as the variable value.

3. Methods

This research employed questionnaires distributed to all employees within the three Credit Unions under study. The questionnaire encompassed inquiries related to Cameron's organizational culture, the UTAUT questionnaire, and custom questions specific to this research. The questionnaire made by the researcher by referring to the construct variables that make up the OC, as seen in Table 1, and combining them with the questionnaire from UTAUT from [44].

Item	Definition	Variable	Questionnaire item
Clan (C)	Close relationship with a member of the organization [13], [14].	1. Teamwork (C1) [45] 2. Empowering (C2) [17]	1. My teammates help me to use IT. 2. IT utilization in the organization enables an employee to accomplish their work.
Market (M)	Define success by gain of market share [13], [14].	1. Competitive (M1) [20] 2. Goal Oriented (M2) [21]	1. IT utilization in the organizations can deliver something different compared to another CU. 2. IT utilization can perform well to achieve the organization's goals.
Adhocracy (A)	Long-term goal and willingness to take a risk [13], [14]	1. Innovative (A1) [46] 2. Taking Risk (A2) [47]	1. Digitalization can accelerate work. 2. The organization takes into account the risks of IT utilization.
Hierarchy (H)	Activity is predictable and controlled [13], [14]	1. Control (H1) [25] 2. Efficiency (H2) [26]	1. IT utilization procedures and policies are controlled. 2. IT utilization can eliminate repetitive work to improve productivity.
Performance Expectancy (PE)	The degree to which the user expects that using the system will help him or her to attain gains in job performance [44]	1. useful to my job (PE1) 2. finish job quickly (PE2) 3. increase my productivity (PE3) 4. makes me get a promotion (PE4)	IT utilization will: 1. useful to my job (PE1) 2. finish job quickly (PE2) 3. increase my productivity (PE3) 4. makes me get a promotion (PE4)
Effort Expectancy	The degree to which users expect to use the system [44]	1. accomplish job quickly (EE1) 2. ease to use (EE2) 3. ease to learn (EE3)	IT Utilization will: 1. accomplish job quickly 2. ease to use 3. ease to learn

		4. ease to become skillful(EE4)	4. ease to become skillful
Social Influence	individual perceives and believes he or she should use the new system [44]	1. Manajer influence me (SI1) 2. Important people influence me (SI2) 3. Influencer influence me (SI3) 4. Climate Organization Influence Me (SI4)	1. Manajer influenced me to use IT 2. Important people influenced me to use IT 3. Influencers influenced me to use IT 4. Climate organizations influence me to use IT
Behavior Intention to Use	The degree of user willingness to use the system [44]	1. Use immediately (BI1) 2. Use overtime (BI2) 3. Use several functions (BI3)	1. I will use IT immediately 2. I will use IT overtime 3. I only use several functions

Table 1. Item Construct for Questioner

A total of 23 questions. The 3 question items are demographic, namely gender, age, and placement. The survey will be administered in English with some explanation to employees unfamiliar with English. The survey was used the Likert Scale, 1 = strong disagree, and 4 = strong agree to avoid neutral choices and force respondents to choose available answers.

A Google Forms questionnaire was distributed to each employee via Whatsapp social media, with a one-month waiting period for responses. 323 data were obtained, and after tabulated there were 35 duplicate data. This is because some employees have more than 1 WA number, resulting in 288 clean datasets for further analysis. Table 2 outlines the demographic details of the respondents.

Gender	
Category	Frequency
Male	186
Female	102
Age	
Categories	Frequency
20 – 30	78
30 – 40 >40	170 40
Placement	
Category	Frequency
CU Mentari Kasih	100
CU Mekar Kasih	23
CU Saun Sibarrung	165

Table 2. Demography of Respondent

According to Table 1, the respondents are dominated by Male, and based on Ages, dominated by generation Y and Z.

3.1. Conceptual Model

The questionnaire data underwent analysis using the SEM-PLS method through Smart-PLS4 software [48]. Three evaluation models were employed—namely, the measurement evaluation model, structural evaluation model, and fit model [43]. The formative calculation of the value driver of OC was then applied to a second-order embedded two-stage approach influencing the construct of the UTAUT model, which were measured reflectively.

According to [1], [10] who found that better to recognize the influence of individuals on technology acceptance through the perspective of OC. Research employing the CVF [10], [13], [49] uses four OC constructs—clan, market, adhocracy, and hierarchy—to evaluate how espoused values within an organization affect the successful adoption of technology. Each construct represents values that motivate individuals and is distributed across six dimensions of OC: dominant character, leadership, employee management, organizational glue, strategy, and success criteria. Values of teamwork and empowerment characterize clan; the market embodies competitive and goals-oriented values; adhocracy reflects values of innovation and risk-taking; and hierarchy is defined by values of control and efficiency [13], [14].

In this study, the focus was on exploring OC as a determinant to individual perception of the UTAUT model. The UTAUT model identifies four independent factors that influence individuals in using IT, namely PE, EE, SI, and FC [44], [50]. This study considered three factors: PE, EE, and SI. FC was excluded as it was found to be unrelated to the behavioral intention to use in the primary model, as it is directly associated with the usage of IT. The first three independent factors—PE, EE, and SI—were driven by their direct relevance to individual expectancy and their connection to behavioral intention to use in the primary UTAUT model.

Derived from the relationship between OC and PE, EE, and SI, our research hypotheses are as follows:

H1: OC positively affects PE, EE, and SI.

The initial hypothesis was expanded by detailing the application of each type of OC to each UTAUT construct, resulting in an extended hypothesis., as shown in Figure 1.

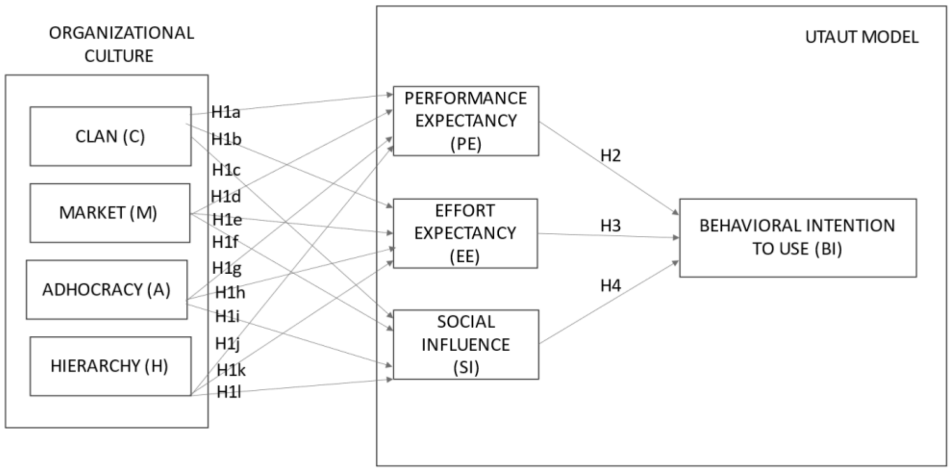

Figure 1. Conceptual Model

H1a: Clan positively affect Performance Expectancy (PE)
H1b: Clan positively affects Effort Expectancy (EE)
H1c: Clan positively affects Social Influence (SI)
H1d: Market positively affects Performance Expectancy (PE)
H1e: Market positively affects Effort Expectancy (EE)
H1f: Market positively affects Social Influence (SI)
H1g: Adhocracy positively affects Performance Expectancy (PE)
H1h: Adhocracy positively affects Effort Expectancy (EE)
H1i: Adhocracy positively affects Social Influence (SI)
H1j: Hierarchy positively affects Performance Expectancy (PE)
H1k: Hierarchy positively affects Effort Expectancy (EE)
H1l: Hierarchy positively affects Social Influence (SI)

This study also employs a predetermined set of hypotheses derived from the extensively used and validated UTAUT model as follows:

H2: PE has positively affected the Behavior Intention (BI)
H3: EE has positively affected the Behavior Intention (BI)
H4: SI has positively affected the Behavior Intention (BI)

4. Results And Discussion

A quantitative method was employed to analyze the OC value drivers [14], PE, EE, SI, and BI [44] . OC was considered an independent variable and measured formative second-order two-stage approach and the UTAUT construct serving as the dependent variable and measured reflectively. The evaluation of the model using SMART-PLS4 encompassed assessing measurement, structural, and goodness-of-fit models [43].

4.1. Measurement Model Evaluation (Outer Model Analysis)

The reflective measurement model, involves a loading factor of ≥ 0.70, composite reliability ≥ 0.70, and average variance extracted (AVE ≥ 0.50), as well as discriminant validity evaluation using Fornell and Larcker criteria below 0.90 [51]. The formative measurement model evaluation considered the significance of outer weights and the absence of multicollinearity among measurement items, as indicated by outer VIF < 5 [51]

Upon conducting the second run of the PLS algorithm, the outer loading remained invalid. For the second calculation, PE1 and EE2 were excluded, see Figure 2.

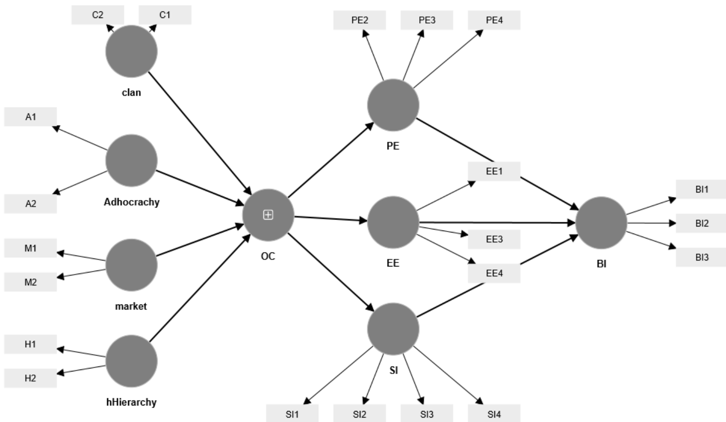

Figure 2. The Model after PE1 and EE2 removed

Figure 2 is a visual representation derived from the SMART-PLS4 model following the exclusion of PE1 and EE2. OC was measured formatively in the second order, indicated by an arrow pointing to the OC variable; according to [51], the computation would be more suitable if the values of the clan, adhocracy, hierarchy, and market variables were utilized to gauge OC, rather than the individual items of each variable (C1, C2, A1, A2, M1, M2, H1, and H2). The other variables (PE, EE, SI, and BI) were assessed reflectively. Table 3 presents the results of the outer loading after the second calculation.

	Outer loadings
A1 <- Adhocracy	0.815
A1 <- OC	**0.519**
A2 <- Adhocracy	0.875
A2 <- OC	**0.622**
BI1 <- BI	0.783
BI2 <- BI	0.913
BI3 <- BI	0.945
C2 <- OC	**0.507**
C2 <- clan	0.794
EE1 <- EE	0.789
EE3 <- EE	0.828
EE4 <- EE	0.712
H1 <- OC	0.704

H1 <- Hierarchy	0.906
H2 <- Hierarchy	0.886
H2 <- OC	**0.643**
M1 <- OC	**0.542**
M1 <- market	0.803
M2 <- OC	**0.636**
M2 <- market	0.861
PE2 <- PE	0.785
PE3 <- PE	0.902
PE4 <- PE	0.894
SI1 <- SI	0.808
SI2 <- SI	0.801
SI3 <- SI	0.798
SI4 <- SI	0.777
C1 <- clan	0.888
C1 <- OC	**0.672**

Table 3. Initial Outer Loading

The blue number represents the formative item. Dealing with invalid formative items involved assessing the significance of outer weights and ensuring no multicollinearity among measurement items, as observed from the outer VIF<5 [51], see Table 4.

	Original sample (O)	VIF	P values
A1 <- OC	0.519	1.233	0
A2 <- OC	0.622	2.009	0
C1 <- OC	0.672	1.221	0
C2 <- OC	0.507	1.394	0
H1 <- OC	0.704	3.097	0
H2 <- OC	0.643	2.045	0
M1 <- OC	0.542	1.431	0
M2 <- OC	0.636	1.775	0

Table 4. Outer Loading Formative Item

Table 4 shows that all formative items exhibit outer loadings exceeding 0.5 and possess significant P values (<0.05) [51]. It is recommended to retain these items in the computation under such circumstances.

4.2. Second-Order Embedded Two-Stage Approach

This method starts by creating data from Figure 3 using SMART-PLS4 [48]. In Figure 3, the process of obtaining the latent variable from the dimension is illustrated. The red square signifies that OC was assessed using the items (C1, C2, A1, A2, M1, M2, H1, and H2) rather than the variable.

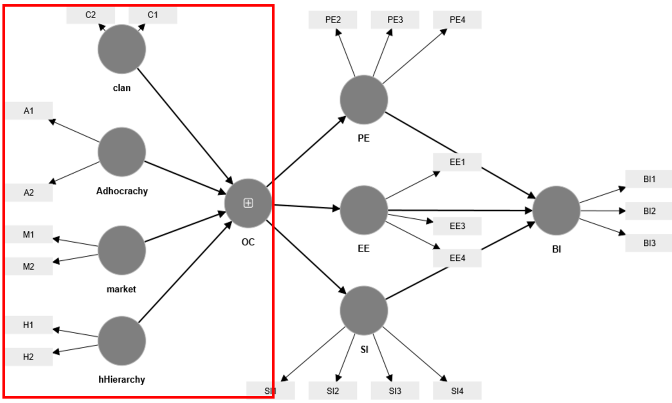

Figure 3. OC Latent Variable

According to [51], this circumstance is not conducive to accurate dimension measurement. Figure 4 depicts the model utilizing latent variables, enhancing the measurement of OC as it employs variables (Clan, Adocracy, Hierarchy, and Market) rather than individual items.

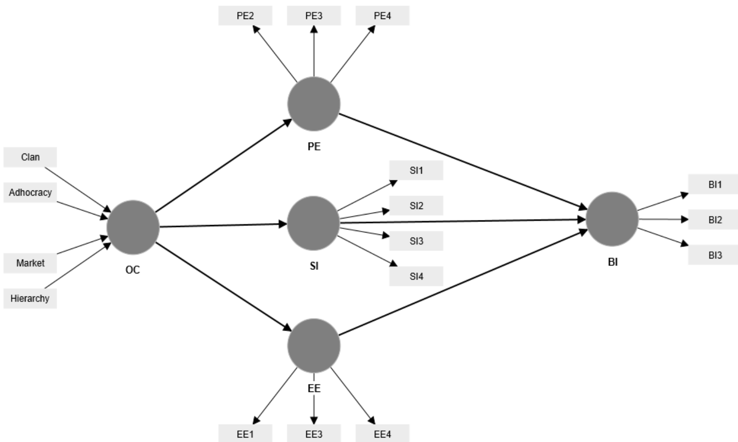

Figure 4. The Final Model

For subsequent calculations, this study utilized the model presented in Figure 4, wherein the values of the items clan, market, hierarchy, and adhocracy were substituted with latent variable values.

Table 5 indicates that the reliability of all variables reached an acceptable level, with an average exceeding 0.70, and the convergent validity (AVE) for each variable surpassed 0.50.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.856	0.876	0.914	0.78
EE	0.671	0.68	0.821	0.605
PE	0.827	0.846	0.896	0.743
SI	0.808	0.812	0.874	0.633

Table 5. Reliability and Validity

When assessing model measurements, aside from outer loading, reliability and validity, and AVE, it is essential to evaluate discriminant validity by examining the Fornell-Lacker criteria and Heterotrait-Monotrait Ratio (HTMT) [43]. Table 6 shows Fornell-Lacker and HTMT results.

	BI	EE	PE	SI
BI	0.883			
EE	0.503	0.778		
PE	0.321	0.525	0.862	
SI	0.627	0.526	0.343	0.796

Fornell-Lacker

	BI	EE	PE	SI
BI				
EE	0.656			
PE	0.37	0.7		
SI	0.749	0.702	0.391	

HTMT

Table 6. Fornell-Lacker and HTMT results

The Fornell-Lacker criterion stipulates that the root AVE of a variable should exceed the correlation with other variables. According to Table 6, the BI variable has a root AVE of 0.883, which is higher than its correlation with EE (0.503) and greater than the correlations with PE (0.321) and SI (0.627). This outcome indicates that the discriminant validity of the BI variable is satisfied. The inclusion of HTMT is presented because this measure of discriminant validity is considered more sensitive or accurate in detecting discriminant validity [43]. The recommended threshold is set below 0.90. The test outcomes indicate that the HTMT value for variable pairs was below 0.90, confirming the attainment of discriminant validity. The variable better explains the variation in the measurement item than the item variable itself.

4.3. Hypotheses

The results from bootstrapping are illustrated in Figure 5, displaying the path coefficient and P-value.

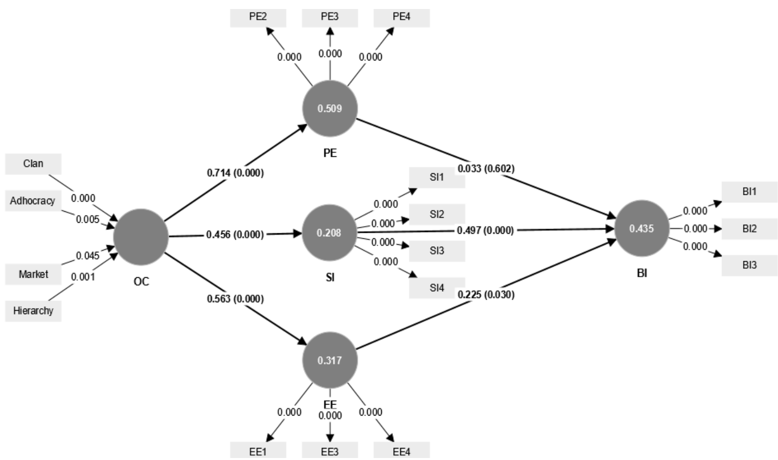

Figure 5. Path Coefficient

Table 7 summarizes the findings from Figure 5, providing comprehensive information, including f-square and confidence intervals, utilized to assess the impact of variables at the structural level.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	f-square	2.50%	97.50%
H3. EE -> BI	0.225	0.24	0.103	2.176	0.03	0.053	0.063	0.468
OC -> EE	0.563	0.568	0.069	8.177	0	0.463	0.433	0.697
OC -> PE	0.714	0.72	0.039	18.076	0	1.037	0.639	0.794
OC -> SI	0.456	0.464	0.049	9.33	0	0.263	0.368	0.559

H2. PE -> BI	0.033	0.04	0.063	0.522	**0.602**	0.001	-0.079	0.17
H4. SI -> BI	0.497	0.479	0.124	4.021	0	0.314	0.221	0.696

Table 7. Hypothesis Result

Referring to Table 6, Hypothesis H2 is rejected due to a p-value > 0.05, whereas H3 and H4 are accepted, indicating a positive influence on BI. The outcomes in Table 6 reveal that OC has a positive impact on PE, EE, and SI. The f-square values are interpreted as follows: 0.02 signifies low, 0.15 signifies medium, and 0.35 signifies high. At the structural level, OC exerts a substantial direct influence on EE with a coefficient of 0.463 (high), on PE with a coefficient of 1.037 (high), and on SI with a coefficient of 0.263 (moderate). This outcome aligns with previous research ([6], [31]) indicating that OC significantly impacts employees' individual use of IT.

Referring to Table 7, a 22% change in the EE variable corresponds to a positive effect of 46% on BI. In comparison, a 49% change in SI results in a positive effect of 69% on BI. Additionally, a 56% change in OC positively influences EE by 69%, a 71% change in OC positively affects PE by 79%, and a 45% change in OC positively impacts SI by 55%. Table 8 depict indirect effect result.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.5%	97.5%
OC -> EE -> BI	0.126	0.134	0.055	2.316	0.021	0.038	0.252
OC -> PE -> BI	0.024	0.028	0.045	0.524	0.600	-0.058	0.118
OC -> SI -> BI	0.227	0.222	0.060	3.800	0.000	0.103	0.334

Table 8. Indirect Effect Result

Table 8, the indirect effects between OC and BI are shown: a 12% change in OC through EE has a positive effect of 25% on BI, and a 22% change in OC through SI has a positive effect of 33% on BI.

Table 9 presents the regression outcomes for the four dimensions of OC concerning PE, EE, and SI. As per Table 9, Hypotheses H1c, H1e, and H1k were refuted, while the rest positively impacted individual perception within UTAUT constructs. Consequently, the researchers obtained support for Hypotheses H1a, H1d, H1g, and H1j, indicating that all OC positively influence PE. Hypothesis H1b, about the clan, and H1h, referring to adhocracy, positively affect EE. Additionally, Hypotheses H1l, H1f, and H1i, corresponding to Adhocracy, Market, and Hierarchy, respectively, positively affect SI.

These findings affirm that the OC adopted significantly impacts IT utilization within the CU. The results also align with existing literature on IT adoption [6], [22], [31]. According to our findings, cultural values such as teamwork, empowerment, competitiveness, goal orientation, innovation, risk-taking, control, and efficiency play a role in shaping an individual's behavior towards accepting IT.

	PE						
	Unstandardized coefficients	Standardized coefficients	SE	T value	P value	2.50%	97.50%
H1j. Hierarchy	0.22	0.22	0.05	4.353	0	0.12	0.319
H1g. Adhocracy	0.311	0.311	0.047	6.568	0	0.218	0.404
H1a. Clan	0.18	0.18	0.048	3.725	0	0.085	0.275
H1d. Market	0.301	0.301	0.05	5.992	0	0.202	0.4

	EE						
	Unstandardized coefficients	Standardized coefficients	SE	T value	P value	2.50%	97.50%
H1b. Clan	0.13	0.13	0.056	2.32	0.021	0.02	0.24
H1e. Market	0.061	0.061	0.058	1.05	**0.295**	0.053	0.176
H1h. Adhocracy	0.476	0.476	0.055	8.691	0	0.368	0.584
H1k. Hierarchy	0.079	0.079	0.058	1.354	**0.177**	0.036	0.194

SI

	Unstandardized coefficients	Standardized coefficients	SE	T value	P value	2.50%	97.50%
H1c. Clan	0.015	0.015	0.062	0.235	**0.814**	-0.107	0.136
H1l. Hierarchy	0.168	0.168	0.064	2.608	0.01	0.041	0.295
H1f. Market	0.219	0.219	0.064	3.413	0.001	0.093	0.346
H1i. Adhocracy	0.235	0.235	0.06	3.895	0	0.116	0.354

Table 9. Regression Result

4.4. Model Fit Measurement

These measurements signify that the model serves as a robust predictive tool, as evidenced by R2, Q2, Standardized Root Mean Square Residual (SRMR), Linearity Check, and FIMIX-PLS. Table 10 is the summarized of the measurement of fit model.

Measure	**Result**
R2	Moderate
Q2	good predictive value
SRMR	achieve fit model
PLS predict	medium predictive power
Linearity	robustness achieved
Fimix	2 segment

Table 10. Summary of Fit Model Measurement

The R2 value indicates that the BI possesses an R square value of 0.435, implying that 43.5% of the variance in BI can be explained by the variables EE, PE, and SI. The changes in the SI variable by 22% can be accounted for by OC, while changes in PE by 52.2% and EE by 35.9% can be explained by OC.

The Q2 value for BI is 0.095, indicating a good predictive performance. The SRMR value of 0.094 suggests a well-fitting model. PLS-Predict indicates a substantial number of significant variables in the PLS calculation, both in terms of RMSE and MAE, surpassing the linear version of the calculation. Therefore, this research model exhibits a moderate level of predictive power. As the model lacks a linear relationship, it attains robustness. The FIMIX-PLS calculation results in two segments, with segment sizes of 65% for segment 1 and 35% for segment 2.

4.5. Discussion

Clan positively impacts PE as per Hypothesis H1a. This hypothesis was supported with a P-value = 0. Clan emphasizes employee personal development, commitment, empowerment, and teamwork, instilling high confidence in employees to contribute optimally to the organization. This reinforces the findings [52], which mention that consensual culture, identifiable by its attributes akin to a clan culture, can potentially enhance employee performance in carrying out their responsibilities.

Clan positively affects EE (H1b). This hypothesis was accepted (P-value = 0.021). Within a clan culture, decisions are commonly reached through unanimous agreement, fostering a robust collaborative mindset [53]. According to [54], [55] this cultural approach cultivates a sense of community, encouraging teamwork and knowledge-sharing among team members. As a result, it promotes a deeper understanding and efficient utilization of emerging technologies, thereby reducing the perceived effort associated with adopting a new system. Additionally, clan cultures exhibit increased adaptability to change, a crucial factor in introducing novel technologies. Individuals in such cultures are more inclined to embrace and integrate new technologies, leading to a decreased sense of effort expectancy.

Clan positively affects SI (H1c). This hypothesis was rejected (P-Value = 0.814). SI pertains to the perception of individuals or employees who deem it significant for others to adopt a new system. In the context of Clan culture, the emphasis on strong collaborations can pose challenges to social influence, especially when the introduced technology is viewed as a deviation from established clan norms and principles. Credit unions introduce Smart CU, an online application for daily shopping; however, findings from the Smart CU questionnaire indicate a lower desirability due to the influence of the general public favoring well-known marketplaces [56].

Market positively affects PE (H1d). This hypothesis was accepted (P-value = 0). This finding is in line with [57], who found that performance in financial organizations such as banks is also influenced by market culture.

Market positively affects EE (H1e). The hypothesis was rejected (P-Value = 0.295). One detrimental outcome of market culture on employees' expected effort is the potential for increased burnout. Burnout refers to employees' fatigue when exerting excessive effort for prolonged periods. In a market culture, employees are consistently encouraged to go above and beyond, motivated by their leaders. This leads team members to strive for skill and knowledge improvement continually. However, the persistent pressure can result in heightened stress and exhaustion, ultimately impacting the anticipated effort negatively. In other words, while market culture may initially inspire employees to exert more effort, the high-stress environment and ongoing pressure can eventually lead to burnout. This, in turn, can lead to decreased productivity and a diminished expectation of effort as employees grapple with sustained elevated stress levels.

Market positively affects SI (H1f). The hypothesis was accepted (P-value = 0.001). Top performers and those quick to embrace technology within market cultures are frequently rewarded, whether through recognition, bonuses, or prospects for career progression. This acknowledgment can magnify the social influence on others, encouraging them to adopt similar technologies. Despite the competitive nature fostered by market cultures, there is a simultaneous emphasis on collaboration to attain organizational objectives. This collaborative aspect cultivates a supportive environment wherein employees aid each other in adapting to and utilizing new technologies, thereby amplifying positive SI.

Adhocracy positively affects PE (H1g). The hypothesis was accepted (P-value = 0). [52] Indicate that the entrepreneurial culture significantly influences the performance of employees in a bank. When examining the attributes of this culture, they align closely with the characteristics of adhocracy culture.

Adhocracy positively affects EE (H1h). The hypothesis was accepted (P-value = 0). Adhocracy cultures frequently offer flexible work arrangements, including options for remote work and adaptable schedules. This flexibility can streamline the integration of technology adoption into employees' work routines, thereby minimizing the perceived effort involved. Furthermore, this culture places a high value on continuous learning and development, fostering employees' positive perception of technology adoption as an opportunity for both personal and professional growth.

Adhocracy positively affects SI (H1i). This hypothesis was accepted (p-value = 0). The Adhocracy culture, characterized by flexibility, innovation, and decentralized decision-making, can positively influence the social influence component. This culture encourages employees to explore new ideas and technologies [58]. The research discovered that an innovative culture can create an environment where employees are more inclined to experiment with and embrace new technologies. They perceive these technologies as tools to enhance their performance and contribute to the organization's success.

Hierarchy positively affects PE (H1j). This hypothesis was accepted (P-value = 0). Bureaucratic culture impacts the PE of the employee in a bank [52]. Bureaucratic culture shares the same attributes as Hierarchy culture.

Hierarchy positively affects EE (H1k). This hypothesis was rejected (P-value = 0.177). Stability and predictability take precedence in hierarchical cultures, often manifesting risk-averse tendencies. Employees may perceive adopting new technologies as risky, potentially leading to errors or disruptions. This perception can increase their expectation of effort as they become more cautious and hesitant.

Hierarchy positively affects SI (H1l). The hypothesis was accepted (p-value = 0.001). Hierarchical cultures can positively impact the UTAUT's social influence by establishing clear communication channels, endorsements from authoritative figures, formalized procedures, norms of conformity, and reducing uncertainty. Additionally, hierarchical cultures implement formal procedures that can facilitate the introduction of new technologies, a crucial aspect within the UTAUT framework.

PE has positively affected BI (H2). This hypothesis was rejected (P-value = 0.602). The usage of Mobile CU in the three CUs, with an average of three hits per day, remains relatively low. CU is still in the early stages of adopting information technology [48] and emphasizes internal infrastructure development more. Moreover, the prevalence of Generation Y employees within CU, who are highly acquainted with information technology, results in PE not significantly influencing the inclination to use applications. This finding is inconsistent with [44] findings. This study's findings align with and reinforce the findings of [59], [60], who found that PE is negative for BI.

EE has positively affected the BI (H3). The hypothesis was accepted (p-value = 0.03). In line with the findings [61], their findings revealed that EER impacts the BI.

SI has positively affected the BI (H4). The hypothesis was accepted (p-value = 0). This result reinforces the findings of [58], [62], [63], who found that individuals believe that influential figures in their surroundings support the adoption of a new system, they are more likely to plan to use that system.

5. Conclusion

The study tested 15 hypotheses, and four were rejected. First, Clan culture does not influence SI because CU's emphasis on collaboration poses a challenge if the implemented technology jeopardizes employees' positions, leading to resistance. Second, market culture does not influence EE as it tends to foster competition, and employees resist change if it exceeds their capabilities. Although market culture is not dominant in CU, this result is crucial for organizational survival. Third, hierarchical culture does not influence EE due to its structured nature hindering adaptability and innovation, leading to higher perceived effort in adopting new technologies. Bureaucratic hurdles, limited autonomy, and resistance to change affect motivation. The last rejected hypothesis is that PE does not influence BI attributed to the dominance of Generations Y and Z who are already familiar with technology and view it as a performance enhancer.

6. Limitation and Future Research

The study has limitations, focusing on for-profit organizations specializing in empowerment and financial loans in Indonesia. The small size and reach of the three CUs, representing two provinces, may introduce bias. The reliance on people's feelings and perceptions for assessments could impact causal relationships. The sample size is convenient, and using two value drivers for each organizational culture dimension may be insufficient. Cameron's OC cannot be used as an exogenous variable due to its calculation procedure. The conceptual model lacks moderating variables, and future research should explore larger organizations, incorporate more value drivers, and specify technology types for precise results. Additionally, qualitative studies can provide a deeper understanding of the impact of OC on employees' perceptions of IT acceptance.

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Comparative Analysis of Machine Learning Techniques for Cryptocurrency Price Prediction

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ABSTRACT

The significant increase in cryptocurrency trading on digital blockchain platforms has led to a growing interest in employing machine learning techniques for the effective prediction of highly nonlinear and nonstationary data, becoming increasingly popular among both individual and institutional market participants. The aim of this research is to deal with the challenging task of predicting the closing prices of two prominent cryptocurrencies, Binance Coin (BNB) and Ethereum (ETH), utilizing machine-learning techniques. This study evaluates the efficacy of various machine learning models in predicting cryptocurrency prices, with a particular focus on Support Vector Machines for Regression (SVR), least-squares Boosting (LSBoost), and Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference System (ANFIS). These models are compared under various metrics. ANFIS models exhibited superior predictive performance on both training and testing datasets based on diverse performance metrics. Comparatively, SVR with a linear kernel demonstrated strong generalization capabilities, particularly on the testing set. LSBoost, while showing promise in training accuracy, indicated results with higher test errors. ANN models maintained a balance between training and testing. This comparison showed the models' effectiveness, particularly the robustness of ANFIS in capturing the volatile cryptocurrency market trends. The experimental data suggest that certain of the above models can be utilized to predict the ETH and BNB closing price in real time with promising accuracy and experimentally proven profitability.

Keywords: Machine learning, Hybrid method, Predictions, Cryptocurrency

1. Introduction

Over the past years, there has been a noticeable shift from traditional printed currency to virtual currency, leading to the emergence of cryptocurrency [1]. Cryptocurrency, a digital form of currency, utilizes intricate encryption algorithms to regulate its units. This cryptographic approach enhances the security of transactions, eliminating the need for centralized institutions like banks and enabling electronic fund transfers [2].

Since the launch of Bitcoin in 2009, cryptocurrencies have rapidly gained popularity as investment assets, despite their volatile nature. The instability in cryptocurrency values arises from various factors, including transaction costs, market sentiment, mining difficulty, alternative coin prices, user demand, and legal considerations [3]. This volatility makes the prediction of cryptocurrency prices a challenging yet critical task for investors aiming to reduce risks and optimize their portfolios [4]. Although the unpredictable nature of cryptocurrencies complicates these predictions, the increasing interest among traders, investors, and financial analysts has spurred numerous attempts to develop intelligent forecasting models. Accurate prediction models are essential for navigating the complexities of the cryptocurrency market, highlighting the ongoing efforts to understand and anticipate price movements in this dynamic field.

When considering time-series forecasting models, there are three primary categories: pure models, explanatory models, and machine learning-based approaches [5]. Pure models, exemplified by methods like Autoregressive Integrated Moving Average (ARIMA), rely solely on past data of the variable under consideration. They are most suitable for stationary and univariate time-series data [6]. In contrast, explanatory models incorporate predictor variables to forecast the target variable into the future. However, due to the nonlinear and nonstationary nature of cryptocurrency prices, making assumptions about data distributions can significantly affect forecasting accuracy. Non-stationary time-series models exhibit shifting statistical distributions over time, leading to variations in the relationship between input and output variables. Machine learning methods utilize the intrinsic non-linear and non-stationary characteristics of data, taking into account the underlying factors that affect the variable being predicted, by including explanatory features [6,7,8].

While both pure and explanatory models have their applications, they come with limitations. These include the requirement for careful examination of the stationarity of time-series data, the need to make assumptions about data distributions, dependence on historical data for accuracy, the necessity for manual selection and evaluation of functions, difficulty in recognizing long-term relationships in the presence of significant volatility, and limited utility for planning and policy-making due to lack of economic theory foundation [6, 9,10,11,12].

On the other hand, the development of machine learning methods is becoming increasingly popular for financial market forecasts, as they offer solutions to overcome the previously mentioned limitations [13]. In recent years, scholars have increasingly turned to machine learning approaches to forecast cryptocurrencies, coinciding with the rapid increase of artificial intelligence across various industries, including finance [14,15,16,17,18]. Despite the volatility of cryptocurrency prices, machine learning strategies excel at capturing long-term dependencies to identify optimal solutions that align with the available data [11]. Unlike traditional linear statistical models, machine learning techniques can capture the nonlinear aspects of cryptocurrency price volatility, as they have inherent learning capabilities [19,20]. Nonlinearity has been integrated into machine learning algorithms for predicting asset prices and returns, resulting in improved predictive accuracy [21,22].

In response to the complexities inherent in forecasting cryptocurrency prices, this study conducts an extensive analysis of state-of-the-art machine learning techniques. It compares the forecasting accuracy of several models, including SVR, LSBoost, ANN, and a hybrid method, ANFIS, focusing on Ethereum (ETH) and Binance Coin (BNB). The choice of these models is based on their unique strengths in addressing the challenges of cryptocurrency price prediction. SVR is employed for its robustness in handling high-dimensional data and capturing non-linear relationships through kernel functions. ANN is utilized for its ability to model intricate, non-linear patterns inherent in financial data. LSBoost is included for its effectiveness in improving predictive performance through iterative corrections and managing complex feature interactions. ANFIS is selected for its integration of neural network learning with fuzzy logic, which allows it to handle uncertainties and model complex, volatile market behaviors. This diverse set of models provides a comprehensive approach to evaluating forecasting accuracy in the dynamic cryptocurrency market.

The results demonstrate that ANFIS outperforms the other models in accuracy. This superiority is evident in the tests conducted with alternative cryptocurrencies, ETH and BNB, where the results were evaluated through different metrics such as RMSE, MSE, and R^2. These metrics provide a comprehensive insight into the predictive accuracy of each model, further corroborating the exceptional performance of ANFIS in the unpredictable cryptocurrency market. This finding underscores the potential of hybrid machine learning methods, particularly ANFIS, in navigating the volatility of digital asset markets and improving investment decisions.

Structured into four main sections, the paper begins with an introduction to the study's goals, followed by a detailed explanation of the methodology in Section 2. Section 3 results and discussion, showcasing the comparative effectiveness of the examined models, while the final section concludes with the implications of the findings for both researchers and practitioners in the field of financial forecasting.

2. Proposed Methodology

The approach outlined in this paper is depicted in Figure 1, illustrating: (1) data collection, (2) preprocessing data, (3) data partitioning for training and testing, (4) the problem formulation involving input-output pairs, (5) employing machine learning techniques to forecast closing prices, and (6) the evaluation metrics utilized.

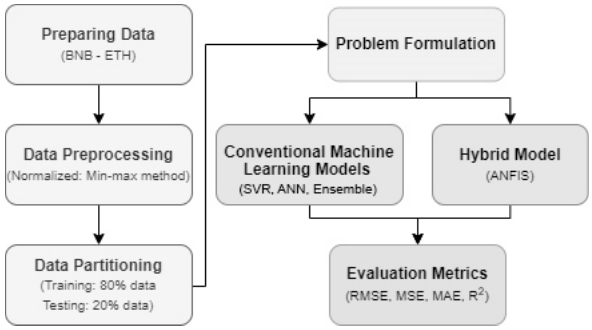

Figure 1. Overview of the suggested approach

2.1. Dataset

Data for the two most capitalized cryptocurrencies, Ethereum (ETH) and Binance Coin (BNB), were collected from coinmarketcap.com, a global portal ranked by market capitalization, providing prices and charts for the top cryptocurrencies. At the time of writing this article, these currencies were among the top five in terms of market capitalization.

This research utilizes daily historical time series data of ETH and BNB closing prices in USD, analyzing datasets for both cryptocurrencies collected from October 1, 2020, to September 30, 2023. This period covers a total of 1,095 observations for each cryptocurrency, providing a comprehensive basis for analysis. The plots of closing prices versus time for ETH and BNB are illustrated in Figures 2a and 2b, respectively.

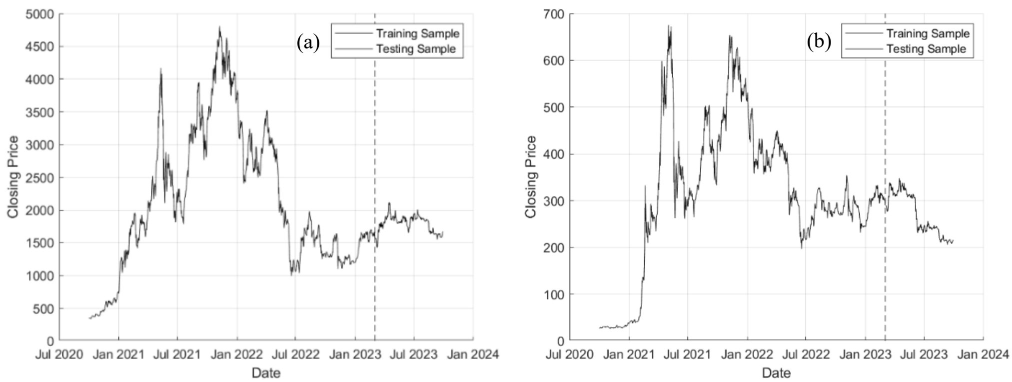

Figure 2. (a) ETH closing price (b) BNB closing price

The dataset has six features, detailed in Table 1. The table outlines characteristics of a cryptocurrency dataset, including daily average, opening, highest, lowest, and closing prices, along with the total volume traded. Each feature is described in terms of its role in representing the day's trading dynamics.

Feature	Description
Price	Average daily price
Open	Day's initial price
High	Peak price of the day
Low	Minimum price of the day
Close	Final price of the day
Volume	Total daily trading volume

Table 1. Features of the cryptocurrency dataset

Both ETH and BNB price series demonstrate non-stationary characteristics, as confirmed by the Augmented Dickey-Fuller (ADF) tests. The results of these tests are detailed in Table 2.

For ETH, the ADF test statistic is -2.206544, not surpassing the critical thresholds for significance levels of 1%, 5%, or 10%, indicating the series is likely non-stationary as we cannot reject the null hypothesis. The accompanying p-value of 0.203879 reinforces this conclusion, suggesting a high probability of a unit root in the series. Similarly, for BNB, the ADF test statistic of -2.364639 fails to exceed critical values,

supporting the non-rejection of the null hypothesis at conventional significance levels and implying non-stationarity. The p-value of 0.151966 further supports the likelihood of a unit root in the BNB closing price series.

	t-Statistic	p-value
ETH	-2.206544	0.203879
BNB	-2.364639	0.151966

Table 2. Augmented Dickey-Fuller test statistic

Following the initial data preparation, the subsequent action entails normalizing the data. This process modifies the data values to conform to a designated range. Utilizing the min-max normalization approach, the data is calibrated to align within a range from 0 to 1, ensuring uniformity and comparability across the dataset. Where y denotes a single point of a feature and Y the feature's vector.

$$y_{rescaled} = \frac{y - \min(Y)}{\max(Y) - \min(Y)}$$

After normalization, the data is divided into training and testing datasets, the first 80% of the collected data allocated for training, and the remaining 20% set aside for testing. The division of the data into training and testing samples is depicted in Figures 2a for ETH and 2b for BNB.

2.2. Problem Formulation

This article focuses on utilizing historical cryptocurrency data, specifically closing price records, to predict future values. The dataset comprises sequential price points, represented as $\{p_0, p_1, p_2, \cdots, p_n\}$, where each p_i corresponds to the price at timestamp i. We define an input window of length w, constructing input vectors v and output o as follows:

$$v = [p_{i-w+1}, p_{i-w+2}, p_{i-w+3}, \cdots, p_{i-1}, p_i]$$

$$o = [p_{i+1}]$$

The objective is to forecast the value of p_{i+1} using an input vector containing past values. The data is organized into pairs of input-output as shown above. For the models discussed in this article, we consider a prediction window of 3 days.

2.3. Conventional machine learning models

In this paper, Support Vector Machine for Regression (SVR), Artificial Neural Networks (ANN), and least-squares Boosting (LSBoost) are employed for analysis. Furthermore, K-fold validation is utilized to ensure the robustness and applicability of the models.

To prevent overfitting, this study adopts K-fold cross-validation. This method divides the training dataset D into, K equal parts, using $K - 1$ parts for training and the remaining part for validation. This cycle repeats K times, each with a different validation set, to produce K models. The final model's prediction is the average of these K models' predictions. In this study, the number of folds in the K-fold cross-validation is set to 5 since it is widely used in practice.

2.3.1. Support Vector Machines for regression (SVR)

Support vector machine (SVM) is a supervised machine-learning technique. The pioneer of SVM was Varpik [23,24]. Initially focused on binary classification, SVM can be extended to regression tasks, known as Support Vector Regression (SVR) [25,26]. In SVR, a kernel function is applied to transform the input data into a higher-dimensional space. This transformation allows SVR to develop a hyperplane that best fits the input vectors to the desired output values [27]. The main idea of SVR is to map data into a high-dimensional feature space. It uses Vapnik-Chervonenkis Dimension theory as its operational foundation to produce an optimal hyperplane that converts a low-dimensional input vector to a higher-dimensional feature space, ensuring high generalization capability [28,29].

Since the challenge of applying an SVR algorithm is selecting the proper kernel function, Linear and Gaussian (Radial Basis Function (RBF)) kernels were applied. The equations for each of the kernels in the SVR algorithm are listed in Table 3.

SVR	Kernel	Description
Linear	$K(x_1, x_2) = x_1^T x_2$	Two class learning.
Gaussian	$K(x_1, x_2) = \exp\left(\frac{-\parallel x_1 - x_2 \parallel^2}{2\sigma^2}\right)$	One-class & multi-class learning.

K: Kernel function
x_1, x_2: Input vectors
σ: Width of the kernel

Table 3. SVR types

2.3.2. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are a highly valuable method for nonlinear data modeling within Artificial Intelligence, integrating mathematics and computations [30,31]. ANNs simulate biological neurons [32,33] through an adaptive system that acquires knowledge using artificial neurons arranged in a multi-layered structure. The fundamental components of an ANN include several processing elements across multiple layers [34]. By utilizing interconnected processing elements (artificial neurons), ANNs process system inputs and generate outputs by applying specific nonlinear functions [32].

The network's artificial neurons are organized into three main layers: input, hidden, and output. In the first layer, each input a_i is assigned a weight w_i, and each artificial neuron receives a bias b_i, treated as an additional input. The effectiveness of a_i is determined by its weight w_i; a higher value indicates a greater impact on the system. The ANN computes the values of weights to establish relationships between input and output data [35]. An activation function computes the sum of the weighted inputs to produce the output [36].

This paper concentrates on the application of a feedforward neural network for regression tasks, utilizing a Multilayer Perceptron (MLP) model. The MLP is a kind of feedforward neural network characterized by its layered structure, where neurons are arranged in multiple layers. Within this architecture, each neuron in a given layer is fully connected to all neurons in the next layer, creating a densely connected network.

2.3.3. Regression Tree Ensembles

Regression tree ensembles are predictive models that are formed by combining multiple individual regression trees, each weighted differently. Least-squares boosting (LSBoost) is one of these ensemble techniques, primarily aimed at minimizing the mean squared error [37]. LSBoost is an ensemble-learning boosting algorithm designed specifically for estimating continuous target variables. In each iteration, it trains a new learner to capture the discrepancy between the observed target values and the aggregated predictions from all previously trained learners [38]. The final output of LSBoost is derived from the combination of predictions across numerous base learners. These base learners are iteratively trained to address the residual error not accounted for by the outputs from preceding learners [39].

2.4. Hybrid Machine Learning Model

ANFIS, a hybrid machine learning methodology that combines the robustness of fuzzy logic with the computational prowess of Artificial Neural Networks (ANN), was introduced by Jang [40]. This integration utilizes the strengths of both domains to enhance the model's ability to: i) raise its capacity for learning the complexities inherent in processes [41], ii) achieve an optimal relationship between the inputs and outputs of a system, iii) approximates the nonlinear functions, with learning capability [42], iv) provide precise mapping between predictor and dependent variables, facilitating accurate predictions [43]. ANFIS has been employed to solve different real-world problems, including time series forecasting and simulation of engineering processes [41,44,45].

2.4.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The primary ANFIS structure comprises Takagi–Sugeno (TKS) inference (or Sugeno first-order FIS) rule-based learning algorithms, and the "IF-THEN rules" are used for generating mapping inputs and outputs mapping. A typical architecture of ANFIS is shown in Figure 3, which consists of five layers. For simplicity, let's assume the structure with two inputs as x_1 and x_2. Then, the rules R_a and R_b in FIS stated as:

$$R_a\text{: } IF\ \ x_1\ \ is\ \ \widetilde{M}_1\ and\ \ x_2\ is\ \widetilde{N}_1\ \text{, THEN}\ \ g_1(x_1,x_2)\ = p_1x_1 + q_1x_2 + r_1$$

$$R_b\text{: } IF\ \ x_1\ \ is\ \ \widetilde{M}_2\ and\ \ x_2\ is\ \widetilde{N}_2\ \text{, THEN}\ \ g_2(x_1,x_2)\ = p_2x_1 + q_2x_2 + r_2$$

where $\widetilde{M}$ and $\widetilde{N}$ are fuzzy sets for x_1 and x_2, respectively. The function $g_i(x_1,x_2)$ which is the output of the system is the first order polynomial with parameters p_i, q_i, r_i $(i = 1, 2)$.

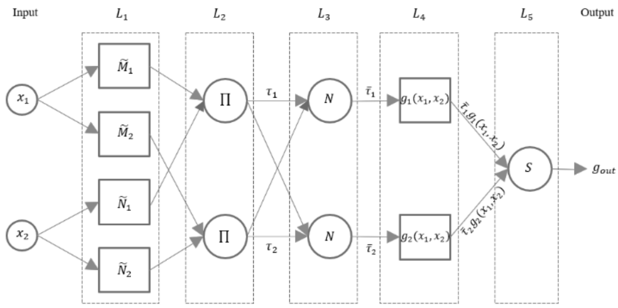

Figure 3. ANFIS structure

ANFIS structure has adaptive (square) and fixed (circle) types of nodes. The output of the *i*th node is defined as $O_{j,i}$. In ANFIS's structure, each layer is described as follows:

L_1 – Fuzzy layer: Fuzzification of inputs, x_1 and x_2, are done in the first layer. The output of the first layer is computed as:

$$O_{1,i} = \mu_{\widetilde{M}_i(x_1)}, \qquad i = 1,2 \tag{1}$$

$$O_{1,i} = \mu_{\widetilde{N}_{i-2}(x_2)}, \qquad i = 3,4 \tag{2}$$

where $\mu_{\widetilde{M}_i(x_1)}$ and $\mu_{\widetilde{N}_i(x_2)}$ are the membership functions of the fuzzy sets $\widetilde{M}_i$ and $\widetilde{N}_i$, respectively.

The inputs are fuzzified by using the triangle membership function described below, the MATLAB function `y=trimf(x,params)` returns fuzzy membership values:

$$f(x;\ \alpha_1,\alpha_2,\alpha_3) = \begin{cases} 0, & x \le \alpha_1, \\ \dfrac{x-\alpha_1}{\alpha_2-\alpha_1}, & \alpha_1 \le x \le \alpha_2, \\ \dfrac{\alpha_3-x}{\alpha_3-\alpha_2}, & \alpha_2 \le x \le \alpha_3, \\ 0, & \alpha_3 \le x \end{cases} \tag{3}$$

where $\alpha = (\alpha_1, \alpha_2, \alpha_3)$ is a triangular fuzzy number.

L_2 – Product layer: The nodes in this layer are fixed ones. The operator is a product marked with (II) that computes the trigger force of a rule in the ANFIS structure. The output of L_2 is computed as:

$$O_{2,i} = \tau_i = \mu_{\widetilde{M}_i(x_1)} \times \mu_{\widetilde{N}_i(x_2)}, \qquad i = 1,2 \tag{4}$$

L_3 – Normalized layer: By the nodes marked with (N) in Figure 3, the outputs in L_2 are normalized. The output of L_3 is computed as:

$$O_{3,i} = \bar{\tau}_i = \frac{\tau_i}{\sum_{i=2}^{2} \tau_i}, \qquad i = 1,2 \tag{5}$$

Also, the nodes in this layer are fixed ones.

L_4 – Defuzzification layer: The output of L_4 is calculated by the multiplication of a first-order polynomial, $g_i(x_1, x_2)$, and normalized firing strength, $\bar{\tau}_i$, as follows:

$$O_{4,i} = \bar{\tau}_i \times g_i(x_1, x_2) = \bar{\tau}_i \times (p_i x_1 + q_i x_2 + r_i), \qquad i = 1,2 \tag{6}$$

The nodes are adaptive in L_4.

L_5 – Total output layer: In the last layer, there is only one fixed node identified as S, which is the output (cumulative sum, Σ) layer. The output of L_5 is generated by:

$$O_{5,i} = g_{out} = \sum_{i=1}^{2} \bar{\tau}_i g_i(x_1, x_2), \qquad i = 1,2 \tag{7}$$

The final output in the ANFIS is a linear combination of consequent parameters.

2.5. Evaluation Performance Metrics

The effectiveness, precision, and reliability of the predictive models are assessed using metrics such as root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R^2). The formulas for these metrics are as follows:

$$RMSE = \left[\frac{1}{N}\sum_{k=1}^{N}\left(Y_k^{pr.} - Y_k^{exp.}\right)^2\right]^{0.5} \tag{8}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left(Y_k^{pr.} - Y_k^{exp.}\right)^2 \tag{9}$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|Y_k^{pr.} - Y_k^{exp.}| \tag{10}$$

where $Y_k^{pr.}$ is the prediction value, and $Y_k^{exp.}$ is the experimental value of kth testing data to be defined from the model, and N is the number of data used in testing.

$$\mathrm{R}^2 = 1 - \frac{\mathrm{RSS}}{\mathrm{TSS}} \tag{11}$$

Where RSS is the sum of squares of residuals. TSS is the total sum of squares, which measures the total variance in the observed data.

3. Results and Discussion

This study emphasizes the development, improvement, and comparative analysis of various machine learning models for cryptocurrency price prediction, with a special focus on deploying the ANFIS model. In the MATLAB environment, customized code for the development of the techniques has been constructed, including SVR with Linear and Gaussian kernels, ANN in the form of MLP, LSBoost, and the ANFIS model. These models offer a comprehensive toolkit for predictive modeling, each with unique capabilities to model complex data relationships.

SVRs, with their different kernels, offer the flexibility to model linear and non-linear relationships in the data. The linear kernel is typically preferred for linearly separable data, enabling straightforward decision boundaries, whereas the Gaussian kernel is suitable for complex, nonlinear data structures, allowing the model to capture intricate patterns. ANNs, particularly MLPs, enabling the model to learn deep representations of the data through layers of neurons and non-linear activation functions. This makes MLPs highly adaptable to various data types and complexities. the LSBoost algorithm enhances prediction accuracy by utilizing the concept of boosting with ensemble regression trees. LSBoost combines multiple weak regression tree models to form a strong predictor, systematically reducing bias and variance by focusing on difficult-to-predict instances. This ensemble method is particularly effective for regression tasks, offering robustness against overfitting and improving predictive performance across diverse datasets. The finding of this paper for SVR, LSBoost and ANN are summarized in Tables 4 and 5 for ETH and BNB, respectively.

ANFIS model combined fuzzy inference systems and neural network methods to enhance the fuzzy inference system structure, resolve deficiencies in neural networks, and increase accuracy and computation speed [46]. To create the fuzzy inference system (FIS) model, the Sugeno-type is employed in the MATLAB neuro-fuzzy toolbox. The FIS was created using the grid partition algorithm. When there are fewer than six input variables, the problem can be solved by using the grid partition algorithm appropriately [47]. For ANFIS learning, a hybrid learning algorithm that makes use of the least square and the gradient method was used. The membership function determines how well each point in the input space is mapped to an acceptable membership value between 0 and 1. The trimf membership function was selected for its simplicity and popularity among scholars [48,49,50]. The ANFIS dataset was trained at 100 epoch iterations with an error tolerance of zero. The finding is summarized in Table 6.

Based on the findings presented in Tables 4, 5, and 6, the following observations are made:

The SVR method demonstrated strong performance, with the linear kernel generally outperforming the Gaussian kernel in terms of lower errors (RMSE, MSE, MAE) and higher (R^2) values across both training and testing phases. This indicates SVR's robustness in linearly separable data scenarios and its capability in generalizing predictions.

Method		**Data type**	**RMSE**	**MSE**	**MAE**	**R^2**
SVR	linear	train	0.0256	0.0007	0.0170	0.9888
		test	0.0091	0.0001	0.0062	0.8992
	Gaussian	train	0.0295	0.0009	0.0204	0.9851
		test	0.0103	0.0001	0.0077	0.8702
LSBoost		train	0.0335	0.0011	0.0243	0.9807
		test	0.0179	0.0003	0.0159	0.6039
ANN		train	0.0282	0.0008	0.0191	0.9864
		test	0.0137	0.0002	0.0107	0.7698

Table 4. Comparative performance of machine learning methods on ETH

Method		**Data type**	**RMSE**	**MSE**	**MAE**	**R^2**
SVR	linear	train	0.0285	0.0008	0.0183	0.9859
		test	0.0099	0.0001	0.0071	0.9783
	Gaussian	train	0.0329	0.0011	0.0202	0.9811
		test	0.0108	0.0001	0.0078	0.9744
LSBoost		train	0.0364	0.0013	0.0254	0.9769
		test	0.0178	0.0003	0.0146	0.9302
ANN		train	0.0346	0.0012	0.0199	0.9791
		test	0.0122	0.0001	0.0093	0.9672

Table 5. Comparative performance of machine learning methods on BNB

The LSBoost method exhibited higher error rates on the test data compared to SVR and ANN. However, its performance varied, with relatively competitive R^2 values, indicating that while it may not consistently outperform other models in precision, it retains some predictive reliability.

The ANN showed balanced performance with a notable capacity for generalization, as indicated by the performance metrics across training and testing datasets. This balance suggests ANN's versatility and potential as a reliable predictive model for cryptocurrency prices.

The ANFIS outperformed conventional models in several key metrics, particularly in achieving lower RMSE and higher R^2 values in the test phase, which highlights its superior generalization capability. The ANFIS model's integration of fuzzy logic with neural networking allows it to effectively capture and model the complex, non-linear relationships typical of cryptocurrency price movements. Figure 4 and 5 comparing predicted and actual cryptocurrency prices for ETH and BNB, respectively. The Figures demonstrate the models' strong fit to the training and testing data suggesting that the model has successfully captured the historical price movements.

Method	Data type	Dataset	RMSE	MSE	MAE	R^2
ANFIS	train	ETH	0.0248	0.0006	0.0163	0.9898
	test	ETH	0.0090	0.0001	0.0062	0.9027
ANFIS	train	BNB	0.0259	0.0007	0.0164	0.9872
	test	BNB	0.0104	0.0001	0.0076	0.9811

Generate FIS: Grid Partition
Train FIS: Hybrid
Function: Constant
Epochs:100

Table 6. Performance of the ANFIS method on ETH and BNB datasets

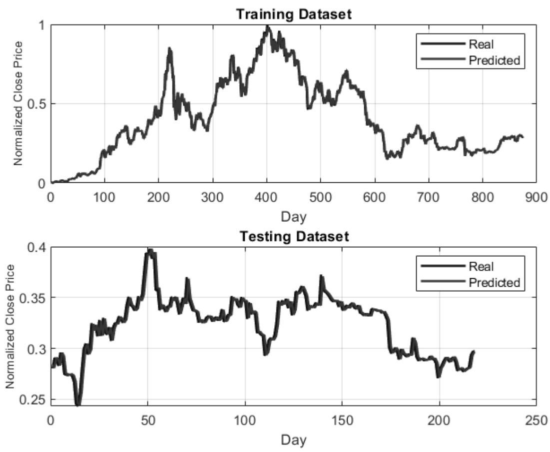

Figure 4. ANFIS model evaluation: real vs. predicted ETH prices in training and testing phases

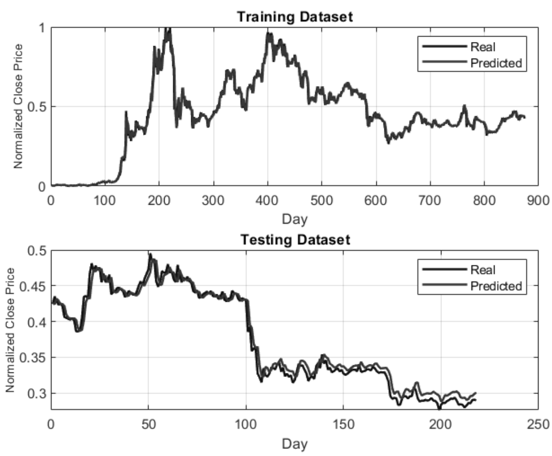

Figure 5. ANFIS model evaluation: real vs. predicted BNB prices in training and testing phases

The analysis indicates that while conventional approaches such as SVR and ANN demonstrate significant predictive power, the hybrid ANFIS model excels in terms of its remarkable accuracy and ability to generalize across various datasets. ANFIS's effectiveness stems from its intricate design, which combines the advantages of fuzzy inference systems and neural networks. This unique architecture makes ANFIS especially suitable for navigating the volatile and unpredictable dynamics of cryptocurrency markets.

The higher test errors observed in LSBoost compared to other models underscore the importance of model selection and parameter optimization in achieving optimal performance. LSBoost's variability in effectiveness suggests that ensemble methods require careful tuning to balance the bias-variance trade-off inherent in predictive modeling.

4. Conclusion

In the dynamic and volatile world of cryptocurrencies, predicting the closing prices of assets is a complex and challenging task. This research set out to address this challenge by applying a various machine learning method, such as SVR, ANN, LSBoost, and ANFIS, to predict the closing prices of BNB and ETH cryptocurrencies. The objective was to compare the accuracy of these models and determine which ones were the most effective for cryptocurrency price prediction.

Based on the findings, this research highlights the effectiveness of hybrid methodologies, particularly ANFIS, in enhancing predictive precision and model generalization, especially within the domain of cryptocurrency price forecasting. The results underscore the importance of employing sophisticated modeling approaches capable of navigating the complex dynamics inherent in financial markets. Moreover, the proven effectiveness of these models indicates a promising opportunity to expand the application of these techniques to additional cryptocurrencies.

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Original Scientific Paper

The Mediating Role of Organizational Trust in the Effect of Social Sustainability on Organizational Resilience: Insights from the Energy Sector

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A B S T R A C T

The purpose of this study is to explore the mediating role of organizational trust in the impact of social sustainability on organizational resilience. Using a sample of 441 employees in the energy sector in Istanbul, a structured questionnaire was applied to measure employees' organizational resilience, organizational trust and perceived social sustainability activities. Data analysis was carried out with SPSS and AMOS 24 programs. Factor analysis and structural equation modeling were used in the study. The data analysis based on path modelling confirms the mediating role of organizational trust in the effect of social sustainability on organizational resilience. The findings show that all social sustainability variables significantly affect all organizational trust dimensions, and organizational trust dimensions significantly affect organizational resilience dimensions. Accordingly, organizational trust dimensions and all social sustainability dimensions have a full mediating variable role in the effect of organizational trust dimensions on organizational resilience dimensions. Future research is important to gain a deeper understanding of the relationships between social sustainability, organizational resilience and organizational trust. In particular, studies in specific sectors or cultural contexts can help us better understand how these relationships may vary and how they may shape organizations' strategies.

Keywords: Organizational Trust, Social Sustainability, Organizational Resilience, Mediating Role

1. Introduction

In today's business world, organizations not only pursue profit but also assume social and environmental responsibilities. In this context, the concept of social sustainability is becoming increasingly important. Social sustainability is considered as an organization's ability to manage and balance its environmental and social impacts [1], [2], [3]. Factors such as businesses promoting ethical practices, supporting social justice and building positive relationships among stakeholders form the basis of social sustainability efforts [4].

To understand social sustainability, it is important to ensure social accountability. This helps to explain more clearly the impact of social sustainability on organizational resilience. Social accountability is the obligation of an organization to be accountable to its stakeholders for fulfilling its social responsibilities and ethical obligations. This concept requires an organization to be transparent and accountable not only for its economic performance but also for its social and environmental impacts [5]. Social accountability involves honoring the rights and expectations of all stakeholders, from employees to customers, suppliers and the community [6]. While this framework helps businesses achieve their social sustainability goals, it also has a significant impact on long-term organizational resilience [7]. Organizational resilience is associated with an organization's capacity to cope with challenges and adapt to changing conditions, and social sustainability practices support workforce engagement and motivation by improving employee well-being, which in turn strengthens the organization's resilience and resilience capabilities [8]. For example, employees working in safe and fair conditions allows the business to experience less labor loss and maintain operational continuity in times of crisis. In this context, it is an important reference point to clearly understand the impact of social sustainability on organizational resilience [9].

Organizational resilience is the ability of organizations to cope with crises, adapt to change and sustain their long-term success [10], [11]. In today's business environment full of uncertainties, organizational resilience is becoming increasingly important. While organizations face challenges arising from various internal and external factors, they can survive and continue to develop thanks to this resilience capability [12]. On the other hand, the concept of organizational trust is also critical for the success of organizations. Organizational trust refers to the process of building and maintaining trust between internal and external stakeholders. A number of factors from leadership interactions to inter-stakeholder relationships affect the formation of organizational trust [13]. Research in the literature reveals that organizational trust has a positive impact on many important outcomes such as organizational performance, collaboration and innovation [14] [15] [16]. In this context, this article aims to examine the impact of social sustainability on organizational resilience through the mediating role of organizational trust. A comprehensive review of the research on the relationships between social sustainability, organizational resilience and organizational trust in the literature can deepen the current understanding of this issue and provide important clues for practice. Another aim of the article is to explain the impact of social sustainability on organizational resilience through organizational trust and to contribute to the development of sustainability strategies in the business world.

2. Literature Review

Social sustainability is the ability of an organization to manage and balance its environmental and social impacts [17]. As part of organizations' sustainability efforts, social sustainability is receiving increasing attention. Social sustainability is a concept that aims to protect and promote values such as social justice, human rights, equality and social welfare, while meeting the needs of a society and taking into account the needs of future generations [18]. Organizational resilience is the ability of an institution or organization to adapt to changing conditions, manage crises, reduce risks and cope with unexpected events. Especially in our age of uncertainty and complexity, resilience is critical for organizations [19]. Social sustainability can affect the resilience of organizations because sustainable practices can help organizations manage environmental and social risks and shape their operations for the future [20]. Organizational trust is defined as the trust that individuals and groups within an organization have in each other, their organization and their leaders. This trust significantly affects the internal communication, cooperation, efficiency and effectiveness of the organization [21]. In the literature, it is stated that organizational trust is influenced by a wide range of factors from leadership interactions to relationships between stakeholders. Research shows that organizational trust has a positive impact on many important outcomes such as organizational performance, collaboration and innovation [22]. In this context, the main claim examined in this article is that the effect of social sustainability on organizational resilience can be explained by the mediating role of organizational trust.

The positive effects of organizational trust in important areas such as organizational performance, cooperation and innovation are frequently emphasized in the literature. Organizational trust strengthens cooperation by increasing trust among employees and contributes to businesses to become more innovative and efficient. For example, [23] states that organizational trust improves employee performance, creates stronger collaboration environments and enables innovative processes to be implemented more effectively. Furthermore, [24] argues that trust plays a key role both in internal organizational relationships and in the organization's interactions with external stakeholders and that in its absence, organizations are more vulnerable to changing conditions.

In this framework, the claim that the effect of social sustainability on organizational resilience can be explained through organizational trust is supported by the literature. Organizational trust can facilitate the adoption of social sustainability practices, making employees more proactive and prepared for crises. [25] emphasizes that organizational trust reinforces employees' belief in long-term cooperation and through this trust, organizations become more resilient in their sustainability strategies. Ensuring social sustainability through practices that promote fairness, equality and employee participation in the workplace contributes to increasing organizational trust and through this trust, organizations become more resilient to change.

At this point, the importance of the research on the relationships between social sustainability, organizational resilience and organizational trust in the literature will be emphasized. In summary, the concepts of social sustainability, organizational resilience and organizational trust are critical for understanding organizations' sustainability efforts, their ability to manage crises and their relationships with stakeholders.

2.1. Analyzing the Impact of Social Sustainability on the Energy Sector

The energy sector is a strategic sector with a wide range of social, environmental and economic impacts. This sector brings along various social and environmental consequences with energy production, distribution and consumption processes. In this context, the impact of the concept of social sustainability on the energy sector constitutes an important research area.

Social sustainability in the energy sector is analyzed in various dimensions. The first is the sustainability and social impacts of the resources used in energy production and supply [26]. For example, the use of fossil fuels, with its environmental and social impacts, is at the center of sustainability debates. Secondly, the impacts of the energy sector on its workers and local communities are analyzed [27]. Activities undertaken for energy production and supply can have significant consequences on issues such as labor employment, community quality of life, health and safety [28]. Third, social acceptance and utilization of innovative practices and technologies in the energy sector are also examined in terms of social sustainability. For example, investments in renewable energy sources can transform society's energy use habits and environmental awareness [29].

Social sustainability studies in the energy sector can also be addressed from an organizational resilience perspective [30]. Organizational resilience examines how energy companies respond to changing market conditions and environmental pressures and sustain their long-term success [31]. Social sustainability enhances the organizational resilience of energy companies by building trust among stakeholders and adapting to societal expectations [32]. In this context, social sustainability efforts in the energy sector can have a significant impact on the future success of the sector and organizations.

2.2. Effects of Organizational Trust on Organizational Resilience

Organizational trust is one of the cornerstones of an organization and plays a critical role in strengthening relationships between internal and external stakeholders. In this context, organizational trust has various effects on organizational resilience [33]. First, organizational trust increases the level of cooperation, communication and interaction within the organization. Creating an environment of trust among employees encourages knowledge sharing and strengthens teamwork. This increases the organization's ability to adapt to changing conditions and act effectively in crisis situations [34]. Second, organizational trust strengthens relationships with external stakeholders and increases corporate reputation. Customers, suppliers, shareholders and other external stakeholders tend to establish longer-term business relationships when they trust the organization. This makes the organization more resilient to external factors and allows it to find support in times of crisis [35]. Thirdly, organizational trust plays an important role in creating organizational culture under the influence of leadership. Leaders' behavior based on the principles of honesty, transparency and justice increases employees' sense of trust and promotes unity and harmony within the organization [36]. The effects of organizational trust on organizational resilience are multifaceted and significantly affect the overall performance of the organization. The existence of trust strengthens the organization's relationships with its internal and external environment and creates a solid foundation in crisis situations. Therefore, it is important to focus on the mediating role of organizational trust to understand the impact of social sustainability on organizational resilience.

3. Research Hypotheses

3.1. Social Sustainability and Organizational Resilience

Sustainability is recognized as an important determinant of corporate performance and long-term success. While social sustainability is defined as the ability of an organization to manage its environmental and social impacts [37], organizational resilience is defined as the ability to resist unexpected changes and turn these changes into opportunities [38]. Social sustainability and organizational resilience are important concepts for today's organizations. Both are considered factors that influence the long-term success of organizations.

Sustainability efforts of organizations can occur in various ways, such as reducing environmental impacts, promoting social justice, and establishing positive relationships among stakeholders. Social sustainability provides a balance between organizations' efforts to fulfill their responsibilities towards society and the environment and maintain their long-term success [39]. On the other hand, in a business environment full of uncertainties, organizational resilience is a critical factor that determines the success of organizations with their ability to adapt to changing conditions and survive in crisis situations [40].

In this context, research focusing on the relationship between social sustainability and organizational resilience has gained importance. It has been suggested in the literature that social sustainability practices can increase organizational resilience [41]. In this context, it is stated that social sustainability practices can strengthen organizational resilience by increasing employees' job satisfaction, commitment and motivation [42]. However, there are limited studies on the mediating role of organizational trust in the effect of social sustainability practices on organizational resilience [43]. It is stated in the literature that organizational trust can increase employees' participation in sustainability practices and therefore affect organizational resilience [44]. Various studies have stated that social sustainability practices increase the performance of businesses and provide long-term competitive advantage [45]. These practices can strengthen organizational resilience by increasing employees' job satisfaction, commitment, and motivation [46]. On the other hand, it is suggested that organizational trust may play a critical mediating role in the relationship between social sustainability and organizational resilience. Research shows that organizational trust can increase employee engagement in sustainability practices, thereby influencing organizational resilience [47]. In light of these findings, the following hypothesis is proposed for the study.

H1: Social sustainability has an effect on organizational resilience.

3.2. Social Sustainability and Organizational Trust

Social sustainability requires an organization to balance its impacts on society and the environment and to take responsibility for a sustainable future [48]. In this context, the activities of the organization should be sensitive to the needs of employees, meet the expectations of society and minimize environmental impacts. Many studies have been conducted that social sustainability practices increase organizational trust. [49] found that social sustainability practices increase employees' organizational trust levels. Similarly, [50] showed in their study that investing in social responsibility projects of enterprises increases employees' organizational trust. In a study conducted by [51], it was observed that employees' organizational commitment and trust increased with the increase in social responsibility practices. [52], in a study on organizational trust, found that organizational trust increases when businesses fulfil their responsibilities to their employees and stakeholders. [53] showed that organizational trust of employees increased with the increase in social responsibility practices of enterprises. [54] found that the trust between suppliers increased with the increase in social responsibility practices of enterprises.

However, some studies on the relationship between social sustainability and organizational trust have revealed different results. For example, [55] suggested that there is no direct relationship between social sustainability practices and organizational trust, but this relationship may be mediated by the transparency and fairness of the business. Similarly, [35] argued that the effect of social sustainability practices on organizational trust is mediated by the corporate reputation of the business. From another perspective, [56] stated that social sustainability practices can increase organizational trust and also have positive effects on organizational commitment and employee satisfaction.

As understood from these studies, the impact of social sustainability practices on organizational trust involves a complex relationship and various factors can affect this relationship. In this context, social sustainability and organizational trust are concepts that feed and strengthen each other. Organizations that adopt social sustainability principles and ensure organizational trust have the potential to be more resilient, innovative and achieve long-term success. In line with these analyses, the following hypothesis was put forward for the study.

H2: Social sustainability has an impact on organizational trust.

3.3. The Mediating Role of Organizational Trust

Organizational trust refers to the trust that employees have in each other and their organizations, and social sustainability practices are among the factors that can increase this trust [57]. In this context, it is argued that as employees' trust in social sustainability practices increases, their access to the resources necessary for organizational resilience may increase and the organization may be more resilient in crisis situations. It is suggested that social sustainability practices can increase organizational resilience by creating an environment of trust within the organization [58]. In this context, some studies in the literature indicate that social sustainability practices improve organizational trust by increasing communication, cooperation and transparency within the business [59]. In particular, the effective implementation of social sustainability practices, together with employees' sense of fairness in management and throughout the organization, can increase organizational trust [60]. Research shows that organizational trust can enable employees to respond more positively to change processes and be more flexible in crisis situations [61]. While social sustainability refers to the capacity of organizations to fulfil their responsibilities towards society and the environment and sustain their long-term success, organizational resilience refers to the ability to resist unexpected changes and turn these changes into opportunities. In this context, the following hypothesis was developed for the study on the mediating role of organizational trust in the literature focusing on the impact of social sustainability on organizational resilience.

H3: Organizational trust has a mediating role in the effect of social sustainability on organizational resilience.

The model of the research is given in Figure 1.

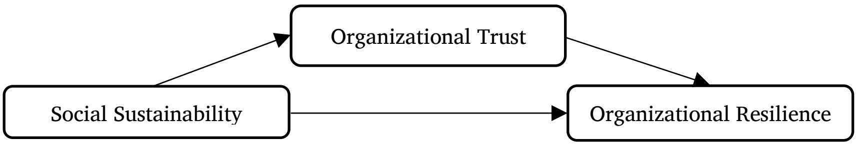

Figure 1. Research Model

4. Materials and Methods

4.1. Sample, Data Collection, Data Analysis, and Ethics Statement

The study group of the research consists of employees in the energy sector operating in Istanbul. According to the 2023 report 'Gender Equality Research in the Turkish Energy Sector' prepared by the German Energy Agency (dena) on behalf of the German Federal Ministry of Economics and Climate Action, the total number of employees in the energy sector in Turkey is 45,276. The sample is a representative subgroup of the population. In order to obtain reliable results in the research, it is necessary to select a sample of appropriate size. In this study, Cochran formula was used to calculate the sample size [62]. However, a more precise sample size can be calculated by applying a correction factor for a universe of 45,276 people, which is the total size of the universe. The corrected sample size is calculated as follows:

$$n = \frac{N \cdot z^2 \cdot p \cdot (1-p)}{e^2 \cdot (N-1) + z^2 \cdot p \cdot (1-p)}$$

Here it is;

- n: Sample size,
- N: Universe size (45,276),
- z: Z value corresponding to the desired confidence level (for example, z = 1.96 for 95% confidence level),

p: Probability of occurrence of the event in the population (50% is accepted, i.e. p = 0.5),

- e: Acceptable margin of error (taken as 5%, i.e. e = 0.05).

As a result of the calculations made according to this formula, the minimum sample size was found to be 382. In this way, it is thought that the sample size to be obtained from the universe of 45,276 people working in the energy sector is sufficient to ensure the reliability of the research.

In this quantitative research, simple random sampling method was used to collect data from 441 energy sector employees. Demographic information of the participants is given in Table 1.

		n	%
Gender	Male	147	33,3
	Female	294	66,7
	Total	441	100,0
Age	29 -	35	7,9
	30-35 years	105	23,8
	36-41 years	133	30,2
	42-47 years	63	14,3
	48 +	105	23,8
	Total	441	100,0
Marital status	Single	91	20,6
	Married	350	79,4
	Total	441	100,0
Education level	High school	14	3,2
	Associate degree	14	3,2
	Undergraduate	133	30,2
	Master	161	36,5
	PhD	119	27,0
	Total	441	100,0
Lenght of work	0-1 year	56	12,7
	2-5 years	84	19,0
	6-10 years	147	33,3
	11-15 years	49	11,1
	16 +	105	23,8
	Total	441	100,0
Total of work	10 -	98	22,2
	11-15 years	168	38,1
	16-20 years	42	9,5
	20 +	133	30,2
	Total	441	100,0

Table 1. Demographic Information of the Participants

Data were collected from the participants through survey questions including demographic questions, social sustainability, organizational resilience and organizational trust scales. Questionnaires were sent online via "Google Forms" to the enterprises selected for data collection. In the questionnaire of the research, there are demographic questions for the personal information of the participants and scale questions for the variables. In the measurement of social sustainability, a scale consisting of 31 items and six dimensions developed by [63] and translated into Turkish by [64] was used. In the measurement of organizational resilience, a scale consisting of 21 items and four dimensions developed by [65] and [66] and translated into Turkish by [67] was used. In the measurement of organizational trust, the scale developed by [68], consisting of 16 items and three dimensions, was used. Social sustainability, organizational resilience and organizational trust scales in the questionnaire were measured using a 5-point Likert scale ranging from "1. Strongly disagree" ... " 5. Strongly agree". The data were collected between November and January 2023.

5. Findings

5.1. Reliability Analysis

According to the cronbach alpha values of general social sustainability, general organizational resilience and general organizational trust variables, it is concluded that the scales are highly reliable. When the reliability of the sub-dimensions of the social sustainability scale is evaluated, it is concluded that the statements belonging to the dimensions of employee participation, employee cooperation and cooperation with the outside are highly reliable, while the statements belonging to the dimensions of equal opportunities, employee development, occupational safety and health are highly reliable. All of the statements belonging to the dimensions of organizational resilience and organizational trust scales are highly reliable. All these results are interpreted depending on the alpha coefficient [69]:

$0.00 \le \alpha < 0.40$, the scale is not reliable,
If $0.40 \le \alpha < 0.60$, the reliability of the scale is low,
$0.60 \le \alpha < 0.80$, the scale is highly reliable and
If $0.80 \le \alpha < 1.00$, the scale is a highly reliable scale.

	Cronbach's alpha coefficient
General social sustainability	0,931
Social sustainability employee engagement	0,781
Social sustainability employee cooperation	0,758
Social sustainability equal opportunities	0,827
Social sustainability employee development	0,837
Social sustainability occupational safety and health	0,807
Social sustainability cooperation with the outside	0,763
General organizational resilience	0,964
Organizational resilience stability	0,938
Organizational resilience backup	0,878
Organizational resilience skill	0,820
Organizational resilience agility	0,889
General organizational trust	0,908
Organizational trust in the friends	0,873
Organizational trust in the manager	0,856
Organizational trust in the organization	0,879

Table 2. Reliability Analysis Results

6. Confirmatory Factor Analysis

6.1. Confirmatory Factor Analysis of the Social Sustainability Scale

The model shown in Figure 2, in which the observed variables Social Sustainability Employee Engagement (SSEE), Employee Co-operation (SSEC), Equal Opportunity (SSEO), Employee Development (SSED), Occupational Safety and Health (SSOSH) and Cooperation with Outsiders (SSCO) are grouped under more than one, unconnected factor, is a first level multifactor model.

In the first level multifactor model shown in Figure 2, there are 20 statements and six factors. There are 31 statements in the scale. As a result of confirmatory factor analysis, 11 statements were removed from the scale because they did not fit the model well. The analysis is continued with the remaining 20 statements. The fit results of the confirmatory factor model are shown in Table 3.

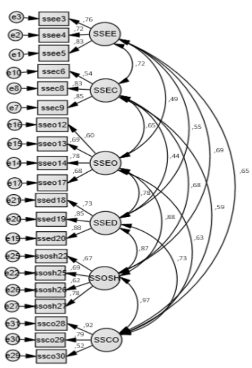

Figure 2. First Level Multifactor Structural Equation Model of Social Sustainability Scale

	ΔX^2	sd	$\Delta X^2/sd$	RMSEA	NFI	CFI	IFI
SSS	463,966*	119	3,90	0,080	0,929	0,945	0,946

$* \, p \leq 0{,}01$

Table 3. Confirmatory Factor Analysis Results of Social Sustainability Scale

Confirmatory factor analysis tests whether the sample data fit the original (constructed) factor structure. The findings of the confirmatory factor analysis are $\Delta X^2 = 463{,}966$, sd = 119, $\Delta X^2/sd = 3{,}90$, RMSEA = 0,080, NFI = 0,941, CFI = 0,945 and IFI = 0,946. This information shows that the result of general model fit (≤ 4-5) shows acceptable fit, and the result of RMSEA, which is the root mean square of approximate errors, which is one of the comparative fit indices, indicates acceptable fit. It can be stated that the model shows acceptable fit according to the result of the normed fit index NFI (0.94-0.90), the model shows good fit according to the result of the incremental fit index IFI (≥ 0.95), and the model shows acceptable fit according to the result of CFI (≥ 0.95).

6.2. Confirmatory Factor Analysis of the Organizational Resilience Scale

The model shown in Figure 3, in which the observed variables of Organizational Resilience Robustness (ORR), Redundancy (ORSTA), Backup (ORB), Skill (ORSKI), Agility (ORA) are gathered under more than one, unconnected factor, is the first level multifactor model.

In the first level multifactor model shown in Figure 3, there are 18 statements and four factors. There are 21 statements in the scale. As a result of confirmatory factor analysis, 3 statements were removed from the scale because they did not fit the model well. The analysis continues with the remaining 18 statements. The fit results of the confirmatory factor model are shown in Table 4.

	ΔX^2	sd	$\Delta X^2/sd$	RMSEA	NFI	CFI	IFI
ORS	460,000*	92	5,00	0,105	0,941	0,950	0,951

$* \, p \leq 0{,}01$

Table 4. Confirmatory Factor Analysis Results of Organizational Resilience Scale

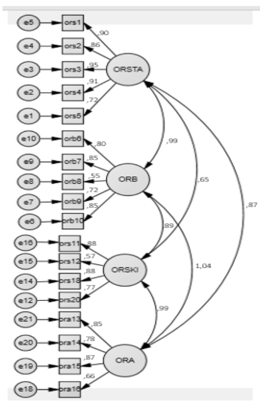

Figure 3. First Level Multifactor Structural Equation Model of Organizational Resilience Scale

The confirmatory factor analysis findings are $\Delta X^2 = 460{,}000$, sd = 92, $\Delta X^2/sd = 5.00$, RMSEA = 0.105, NFI = 0.941, CFI = 0.941 and IFI = 0.946. This information shows that the general model fit (≤ 4-5) result shows acceptable fit, while the RMSEA result, which is the root mean square of the approximate errors, which is one of the comparative fit indices, indicates poor fit. The values of the index 0.10 and above indicate poor fit [70]. According to the result of the normed fit index NFI (0.94-0.90), which is another comparative fit index, it can be stated that the model shows acceptable fit, according to the result of the incremental fit index IFI (≥ 0.95) the model shows good fit, and according to the result of CFI (≥ 0.95) the model shows acceptable fit.

6.3. Confirmatory Factor Analysis of the Organizational Trust Scale

The model shown in Figure 4, where the observed variables such as Organizational Trust, Trust in the Friends (OTTF), Trust in the Manager (OTTM), Trust in the Organization (OTTO), are collected under more than one, unconnected factor, is a first-level multi-factor model.

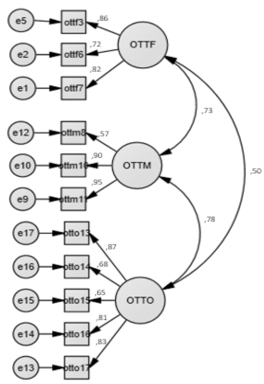

Figure 4. First Level Multifactor Confirmatory Factor Model of Organizational Trust Scale

There are 11 expressions and three factors in the first-level multifactor model shown in Figure 4. There are 17 statements in the scale. As a result of confirmatory factor analysis, six statements were removed from the scale because they did not fit the model well. The analysis continues with the remaining 11 statements. The fit results of the confirmatory factor model are shown in Table 5.

	ΔX^2	sd	$\Delta X^2/sd$	RMSEA	NFI	CFI	IFI
OTS	101,867*	24	4,24	0,08	0,973	0,979	0,979

$*$ p $\leq$ 0,01

Table 5. Confirmatory Factor Analysis Results of Organizational Trust Scale

Confirmatory factor analysis findings show that ΔX^2 = 101,867, sd = 24, ΔX^2/sd = 4,24, RMSEA = 0,08, NFI = 0,941, CFI = 0,941 and IFI = 0,946. This information indicates that the overall model fit ($\leq$4-5) result shows an acceptable fit, and the RMSEA result, which is the root mean square of the approximate errors, which is one of the comparative fit indices, indicates an acceptable fit. It can be stated that the results of normed fit index NFI ($\geq$0.95), incremental fit index IFI ($\geq$0.95) and CFI ($\geq$0.95) from other comparative fit indices show good fit.

7. Mediation Test with AMOS

Whether a third variable mediates the relationship between two variables or whether there is an indirect effect is proved by regression analyses. The following three regression analyses are required.

- In the first analysis, social sustainability is taken as the independent variable and organizational resilience as the dependent variable. Thus, the first condition is investigated.
- In the second analysis, the effect of social sustainability on organizational resilience is investigated. Thus, it is examined whether the second condition is met.
- In the third analysis, social sustainability and organizational resilience are taken as independent variables and their effects on organizational trust are examined. In this case, if organizational trust has an effect on organizational resilience and the effect of social sustainability in the first equation is significantly and significantly reduced, it can be said that organizational trust has a mediating role in the effect of social sustainability on organizational resilience.

The reason why structural equation modelling is preferred instead of regression analysis when investigating the mediation effect is that the structural model provides a stronger infrastructure. While the averages of the variables are used in regression analysis, the structural equation model includes measurement and residual errors in the calculation.

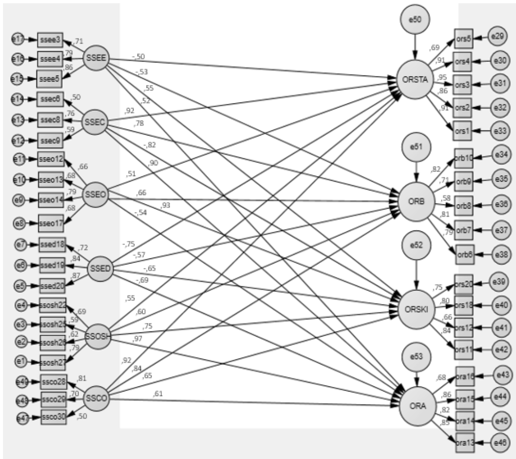

Figure 5. Test Result of the First Model

The fit indices obtained as a result of the model test show that the model is within acceptable limits $\Delta X^2 = 2.400$, sd = 493, $\Delta X^2/sd = 4.86$, RMSEA = 0.07, GFI = 0.890, CFI = 0.956 and IFI = 0.936). The standardized beta, standard error and significance values of the paths from each social sustainability variable to organizational resilience are shown in Table 6. According to the findings, all social sustainability dimensions have a significant effect on organizational resilience. Therefore, the first condition is fulfilled.

Path			**Standardize β**	**Standard error**	**P**
SSEE	→	**ORSTA**	-0,50	0,061	0,000
SSEE	→	**ORB**	-0,53	0,097	0,000
SSEE	→	**ORSKI**	0,55	0,090	0,013
SSEE	→	**ORA**	0,52	0,152	0,014
SSEC	→	**ORSTA**	0,92	0,134	0,050
SSEC	→	**ORB**	0,78	0,222	0,043
SSEC	→	**ORSKI**	-0,82	0,229	0,000
SSEC	→	**ORA**	0,90	0,550	0,000
SSEO	→	**ORSTA**	0,51	0,065	0,000
SSEO	→	**ORB**	0,66	0,100	0,000
SSEO	→	**ORSKI**	0,93	0,103	0,010
SSEO	→	**ORA**	-0,54	0,159	0,015
SSED	→	**ORSTA**	-0,75	0,072	0,018
SSED	→	**ORB**	-0,57	0,104	0,001
SSED	→	**ORSKI**	-0,65	0,121	0,000
SSED	→	**ORA**	-0,69	0,244	0,050
SSOSH	→	**ORSTA**	0,55	0,154	0,016
SSOSH	→	**ORB**	0,60	0,223	0,000
SSOSH	→	**ORSKI**	0,75	0,245	0,000
SSOSH	→	**ORA**	0,97	0,426	0,000
SSCO	→	**ORSTA**	0,92	0,103	0,000
SSCO	→	**ORB**	0,84	0,149	0,000
SSCO	→	**ORSKI**	0,65	0,145	0,000
SSCO	→	**ORA**	0,61	0,240	0,000

Table 6. Path Coefficients of Model 1

In the second model shown in Figure 6, social sustainability dimensions are taken as independent variables, organizational resilience dimensions as dependent variables and organizational trust as mediating variable. Thus, the existence of the second and third effects stated by [71] is investigated.

The fit indices obtained from the test of the model shown in the figure indicate that it is within acceptable limits $\Delta X^2 = 4.125$, sd = 909, ΔX^2/sd = 4.54, RMSEA = 0.06, GFI = 0.885, CFI = 0.964 and IFI = 0.925). The standardized beta, standard error and significance values of the paths specified in the model are shown in Table 7.

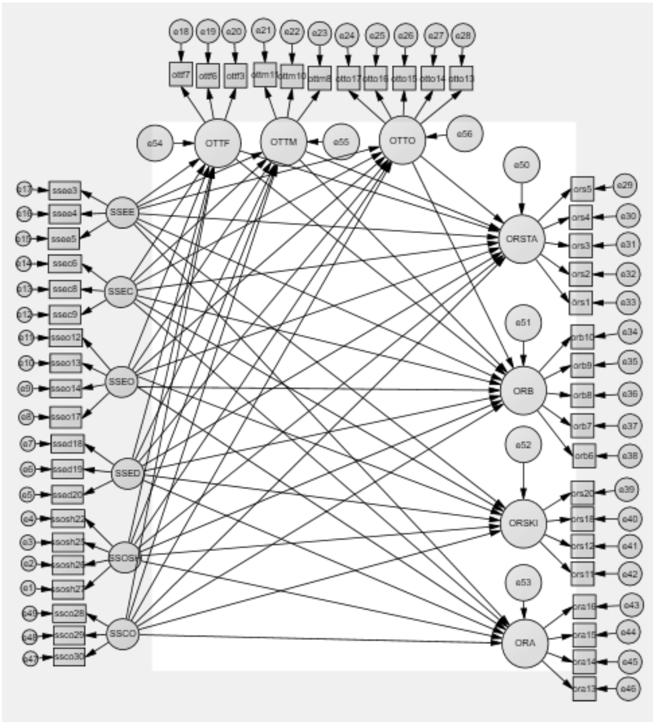

Figure 6. Test Result of the Second Model

Path			Standardize β	Standard error	p
SSEE	→	**ORSTA**	-0,48	0,054	0,320
SSEE	→	**ORB**	-0,50	0,080	0,400
SSEE	→	**ORSKI**	0,45	0,085	0,300
SSEE	→	**ORA**	0,50	0,150	0,250
SSEC	→	**ORSTA**	0,85	0,100	0,450
SSEC	→	**ORB**	0,65	0,200	0,178
SSEC	→	**ORSKI**	-0,75	0,220	0,369
SSEC	→	**ORA**	0,67	0,548	0,546
SSEO	→	**ORSTA**	0,46	0,060	0,140
SSEO	→	**ORB**	0,55	0,099	0,125
SSEO	→	**ORSKI**	0,81	0,100	0,100
SSEO	→	**ORA**	-0,50	0,148	0,150
SSED	→	**ORSTA**	-0,70	0,070	0,180
SSED	→	**ORB**	-0,50	0,100	0,100
SSED	→	**ORSKI**	-0,60	0,111	0,250
SSED	→	**ORA**	-0,55	0,240	0,500
SSOSH	→	**ORSTA**	0,53	0,150	0,160

SSOSH	→	**ORB**	0,52	0,220	0,100
SSOSH	→	**ORSKI**	0,70	0,200	0,105
SSOSH	→	**ORA**	0,90	0,410	0,101
SSCO	→	**ORSTA**	0,87	0,100	0,260
SSCO	→	**ORB**	0,73	0,109	0,175
SSCO	→	**ORSKI**	0,59	0,102	0,482
SSCO	→	**ORA**	0,56	0,125	0,763
SSEE	→	**OTTF**	0,51	0,187	0,002
SSEE	→	**OTTM**	0,91	0,113	0,000
SSEE	→	**OTTO**	0,85	0,091	0,000
SSEC	→	**OTTF**	0,94	0,227	0,000
SSEC	→	**OTTM**	0,72	0,110	0,050
SSEC	→	**OTTO**	0,54	0,126	0,050
SSEO	→	**OTTF**	0,53	0,286	0,050
SSEO	→	**OTTM**	0,59	0,111	0,000
SSEO	→	**OTTO**	0,69	0,090	0,000
SSED	→	**OTTF**	-0,56	0,154	0,000
SSED	→	**OTTM**	-0,54	0,086	0,000
SSED	→	**OTTO**	-0,82	0,091	0,000
SSOSH	→	**OTTF**	0,91	0,666	0,018
SSOSH	→	**OTTM**	-0,95	0,162	0,000
SSOSH	→	**OTTO**	0,56	0,122	0,007
SSCO	→	**OTTF**	-0,74	0,513	0,000
SSCO	→	**OTTM**	-0,55	0,126	0,008
SSCO	→	**OTTO**	0,62	0,120	0,008
OTTF	→	**ORSTA**	-0,63	0,097	0,000
OTTF	→	**ORB**	-0,65	0,100	0,002
OTTF	→	**ORSKI**	-0,66	0,120	0,006
OTTF	→	**ORA**	0,55	0,213	0,016
OTTM	→	**ORSTA**	0,84	0,100	0,000
OTTM	→	**ORB**	0,54	0,096	0,000
OTTM	→	**ORSKI**	0,57	0,119	0,000
OTTM	→	**ORA**	0,68	0,145	0,000
OTTO	→	**ORSTA**	-0,86	0,133	0,000
OTTO	→	**ORB**	-0,92	0,175	0,000
OTTO	→	**ORSKI**	-0,73	0,180	0,000
OTTO	→	**ORA**	-0,86	0,303	0,012

Table 7. Path Coefficients of Model 2

8. Discussion

According to the findings, all social sustainability variables significantly affect all organizational trust dimensions, and organizational trust dimensions significantly affect organizational resilience dimensions. These results are in line with other studies in the literature, but also exhibit some differences. First of all, the positive effect of employee participation and cooperation on organizational trust has been reported in previous studies [72]. It has been observed that these variables increase employees' trust in the organization and thus strengthen intra-organizational relationships. The findings that social sustainability factors such as equal opportunities and employee development also increase organizational trust are supported by various studies in the literature [73]. These factors increase organizational trust by making employees feel fairness and equal opportunity within the organization. Investments in occupational safety and health have been observed to increase employee trust and thus strengthen organizational resilience [74]. Employees' feeling physically and psychologically safe forms the basis of organizational trust and increases the resilience of the organization in times of crisis. Finally, the impact of collaboration with external stakeholders on organizational trust and resilience is a less researched area [75]. However, it can be argued that effective communication and collaboration with external stakeholders enables the organization to be in harmony with its external environment and to be more resilient to external shocks.

In this context, the effects of social sustainability factors on organizational trust and resilience are complex and multifaceted. Our study can be considered as an important step in understanding the relationships between these factors and can shed light on future research.

In addition to all these, with the inclusion of organizational trust dimensions in the model, the effects of all social sustainability dimensions on organizational responsiveness dimensions became insignificant. Accordingly, the result that organizational trust dimensions have a full mediating variable role on the organizational responsiveness dimensions of all social sustainability dimensions seems to be consistent with some studies in the literature. For example, [76] found that organizational trust plays an important mediating role on organizational responsiveness and resilience. This finding highlights that organizational trust is a critical tool for disseminating the results of social sustainability efforts throughout the organization.

In light of these findings, organizations should focus on strengthening organizational trust in order to effectively carry out social sustainability efforts and increase organizational responsiveness. Organizational trust dimensions such as trust in colleagues, trust in manager and trust in the organization can support employees' engagement in social sustainability efforts and the effective implementation of these efforts throughout the organization. In conclusion, it is important to understand and manage the relationship between social sustainability efforts and organizational trust in order for organizations to achieve their sustainability goals and be resilient to crises.

Within the scope of these results, hypothesis 1 (Social sustainability has an effect on organizational resilience), hypothesis 2 (Social sustainability has an effect on organizational trust) and hypothesis 3 (Organizational trust has a mediating role in the effect of social sustainability on organizational resilience) are accepted. As a result, when employees participate in all business processes and cooperate with them about their work, when they are treated equally in processes such as recruitment and remuneration, when plans are made for the development of employees, when attention is paid to their occupational health and safety, when the organization cooperates with students, former employees, and other institutions to ensure the development of its employees, the organization can achieve its goals by operating on a more solid basis, developing strategies in the face of alternative opportunities and unexpected events, and implementing them quickly, and thus employees trust their colleagues, managers and the organization.

9. Conclusion

In this study, the effects of social sustainability variables on organizational trust and organizational resilience were examined. The findings reveal that social sustainability factors significantly affect all organizational trust dimensions and organizational trust also has a significant effect on organizational resilience dimensions. It has been observed that social sustainability factors such as employee participation, collaboration, equal opportunities, employee development and occupational health and safety increase employees' trust in the organization. This trust strengthens intra-organizational relationships and makes the organization more resilient to crises. It was also found that organizational trust plays an important mediating role in the spread of social sustainability practices throughout the organization. As a result, the relationships between social sustainability and organizational trust and resilience require the development of more participatory and collaborative strategies in business processes. The findings of this study suggest that organizational trust is a critical element supporting sustainability efforts and sheds light on strategic planning in this area.

Social sustainability emphasizes that businesses today should focus not only on environmental factors but also on social and economic dimensions. This study shows that social sustainability practices have the potential to increase the resilience of organizations. Social sustainability factors such as employee involvement, cooperation, equal opportunities, employee development, occupational safety and health, and external cooperation can support organizations to be resilient to crises and adapt to change. Organizational trust dimensions such as trust in colleagues, trust in manager and trust in the organization can ensure that social sustainability practices are adopted and effectively implemented by employees. This may increase the organization's ability to cope with crises and its long-term sustainability. In this context, when developing sustainability strategies, organizations should not only focus on environmental factors, but also consider social dimensions such as encouraging employee participation, providing equal opportunities and supporting an environment of trust. Understanding the impact of social sustainability practices on organizational resilience and explaining this impact through organizational trust is of strategic importance for businesses.

The findings obtained in line with the hypotheses put forward within the scope of this study are evaluated as follows: H1 hypothesis, i.e. 'Social sustainability has an impact on organizational resilience' is accepted. It was found that social sustainability practices increase organizations' resilience against crises. H2 hypothesis, i.e. ‘Social sustainability has an impact on organizational trust’ was also supported. Social sustainability factors strengthened employees' trust in the organization. Finally, H3 hypothesis, i.e. ‘Organizational trust plays a mediating role in the effect of social sustainability on organizational resilience’ was accepted. The findings of the study show that organizational trust plays an important mediating role in the relationship between social sustainability and organizational resilience. In the light of these findings, it is concluded that social sustainability practices not only strengthen organizational trust but also make the organization more resilient to crises.

10. Implications

The mediating role of organizational trust is critical for understanding the impact of social sustainability on organizational resilience. The presence of trust strengthens the organization's relationships with its internal and external environment and provides a solid foundation in crisis situations. Future research is important to gain a deeper understanding of the relationships between social sustainability, organizational resilience and organizational trust. In particular, studies in specific sectors or cultural contexts can help us better understand how these relationships may vary and how they may shape organizations' strategies. These implications offer important clues for strengthening organizations' sustainability efforts and responding more effectively in crisis situations. Understanding the mediating role of organizational trust can help organizations to be more successful in the areas of social sustainability and organizational resilience.

There are several examples of literature examining the impact of trust between employees on social sustainability and organizational resilience in the healthcare sector. These studies highlight how organizational trust in healthcare supports high quality patient care and organizational resilience. One study found that organizational trust plays a central role in ensuring high quality patient care and directly contributes to improved patient outcomes. The research showed that increased trust among employees leads to increased patient safety, making the organization more resilient in times of crisis [77]. In a study conducted among nurses, it was found that in units with high levels of organizational trust, employee commitment and satisfaction increased social sustainability, which had positive effects on the quality of care. Patient satisfaction also increased significantly in these units. The study emphasizes that organizational trust has a great impact on the long-term resilience of healthcare organizations [78]. A comparative study conducted in public and private sector hospitals revealed that the effects of organizational trust on social sustainability differ. In private hospitals, trust translates more quickly into customer satisfaction and service quality, whereas in public hospitals, long-term employee commitment and social sustainability effects were observed stronger. In both contexts, trust has proven to be a supportive factor for organizational resilience and sustainability [79].

The search for additional variables that could further clarify the relationships between social accountability, trust and resilience has led to important findings in the literature. In particular, the effects of leadership styles on organizational trust and how these shapes social sustainability practices in different contexts have been examined in both non-profit and educational institutions. In a study examining the effects of leadership styles on organizational trust, transformational leadership style was found to increase trust among employees and this trust led to the adoption of social sustainability practices [80].

In a study examining the impact of leadership styles on social sustainability and organizational trust in educational institutions, it was found that democratic leadership increases trust among teachers and other employees and this trust supports long-term resilience [81]. It has been stated that when nonprofit leaders adopt a fair, transparent and accountable management approach, the resilience of the organization in times of crisis increases significantly [82]. A study examining the relationship between stakeholder engagement and leadership styles in nonprofit organizations found that participative leadership style reinforces trust between stakeholders and employees and this trust strengthens organizational resilience [83].

11. Limitations and Future Directions

This study has some limitations and some suggestions can be made for future research. Firstly, this study focused on a specific sector or type of organization. In the future, in-depth studies can be conducted on specific sectors or types of organizations. For example, similar research can be conducted in different areas such as technology sector or public sector and the results can be compared. Secondly, although this study focused on the mediating role of organizational trust, the effect of other variables may have been ignored. Future research could focus on examining the effect of other factors such as leadership styles, corporate culture and organizational structure. Third, this study highlighted the mediating role of organizational trust on social sustainability and organizational resilience. However, qualitative research could be conducted to better understand the complexity of this relationship. For example, in-depth interviews can help us better understand how organizational trust is built and how it acts. For the future, more research should be conducted in the areas of social sustainability, organizational resilience and organizational trust. This study has been an important step towards understanding organizations' sustainability efforts and their ability to respond more effectively in crisis situations. However, more comprehensive and in-depth research in these areas can make significant contributions to the business and academic literature. In conclusion, although this study has highlighted the mediating role of organizational trust on social sustainability and organizational resilience, future research is expected to provide a broader perspective and deepen knowledge in these areas. In this way, new strategies can be developed to enable organizations to improve their sustainability efforts and respond more effectively in crisis situations.

Ethics Statement: According to the related provisions of the human survey, this study was approved by the Ethics Committee of Istanbul Gelisim University. In the process of survey, we told the interviewees that all the oral and written materials would be recorded and kept confidential. All participants were conducted anonymously, and the results will be used for academic research only, not for commercial purposes. We fully respected the wishes of the interviewees.

Credit Authorship Contribution Statements

Ayşegül Özkan: Writing - review & editing, writing - original draft, conceptualization, methodology, data analysis and writing.
Ayşe Meriç Yazıcı: Writing - review & editing, writing - original draft, conceptualization, methodology.

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A Semantic-Context Embedding Enhanced Attention Fusion BiLSTM: Unraveling Multilingual Sentiments in Product Reviews with Advanced Deep Learning

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A B S T R A C T

For natural language processing (NLP), sentiment analysis (SA) is crucial since it helps to understand users' feelings and opinions in a variety of contexts. Even though Deep Learning (DL) techniques are becoming more popular in SA, effective model optimization can be difficult because they frequently call for a great deal of hyperparameter tuning. However, because current models can't sufficiently capture the variety of review contexts, it introduces bias and inaccuracies, especially in product reviews. For Multilingual Sentiment Analysis (MSA) in product reviews, this research proposed a Semantic-Context Embedding Enhanced Attention Fusion BiLSTM (SCEEAF-BiLSTM). The proposed model combines Continuous Bag-of-Word (CBoW) and Skipgram techniques to extract semantic context after the preprocessing stages of tokenization, stop word removal, and case normalization. A novel Convolutional BiLSTM with Enhanced Attention (CoBLEA) architecture is introduced for multilingual sentiment prediction to extract comprehensive context representations. The model ultimately shows efficacy in dividing multilingual sentiments into positive, neutral, and negative states, providing a viable method for complex SA in several circumstances. The outcome signifies that the proposed approach obtains a high accuracy attained 0.987, precision attained 0.985, recall attained 0.978 and F1-Score attained 0.986 when compared with prior works. With practical applications in sentiment-driven platforms operating in multiple languages, the research presents a method for complex SA in e-commerce, social media, and customer feedback systems. It also emphasizes the significance of comprehending multilingual opinions for enhancing marketing strategies, driving business decisions, and improving customer satisfaction.

Keywords: Sentiment analysis, tokenization, Embedding, Convolution neural network (CNN), Bidirectional Long Short-Term Memory (BiLSTM)

1. Introduction

Social media has arisen as a dominant infrastructure for online communication, allowing individuals to express their thoughts and emotions in real-time [1]. To decipher people's emotional state, attitudes, and sentiments from their written language, sentiment analysis (SA) thus becomes essential [2]. In addition, SA is a valuable instrument for examining the public's response to political issues. The political parties' decisions are influenced by public sentiment. Because of its significance, one of the most popular NLP subjects is SA [3]. The range of tasks that NLP solves is quite wide. For example, NLP can be used to build automatic systems like Machine Translation (MT), voice recognition, named entity identification, SA, question-answering, autocompletion, text prediction, text classification, summarization, and so on [4]. One of the important tasks of NLP is considered by the name opinion mining or SA. SA is an attempt at a text's subjective elements, such as feelings, humor, confusion, mistrust, etc., that are intended to be extracted via SA [5-6].

An application known as SA uses text analytics to determine the polarity of a given body of text, including neutral, positive, and negative sentiments. SA serves as a measure of public opinion by forecasting public opinion on a given topic, especially from a political and economic point of view. Businesses can use SA, for instance, to learn what customers like and dislike about their goods and services and then adjust their marketing strategies accordingly. This can ultimately result in increased sales and profitability [7].

Due to the wealth of resources available, SA research has mostly concentrated on texts written in a single language, such as English. However, SA methods created for single-language tasks might overlook details in multilingual texts [8]. Consequently, it takes focused work to develop models that support multiple languages. The complexity and challenges of MSA become more significant when analyzing non-English data. There is potential for improvement in this task because of mechanisms that either favor translating to English or rely on limited resources [9]. The development of multilingual and interoperable techniques and solutions to function in a wider context is becoming more and more crucial as multilingual and intercultural societies arise [10].

MSA approaches frequently employ MT-based techniques or combine monolingual datasets from various languages to produce extensive multilingual datasets that can be used for Machine Learning (ML)-based sentiment classification [11]. Nevertheless, certain techniques might not be effective for texts that contain multiple languages, and certain techniques might only apply to one language. Furthermore, a labeled dataset is necessary for supervised ML, which makes manual data labeling methods costly and time-consuming [12]. Prior research in ML has concentrated on the application of MT systems for knowledge transfer from languages with plenty of assets to individuals with scarce assets [13]. These techniques usually entail sentiment classification using ML techniques and text translation from under-resourced languages into English. However, these approaches frequently have drawbacks, such as poor translation quality and meaning loss [14]. Recent developments in NLP have demonstrated that DL methods like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Adversarial Neural Networks (ANN), and Generative Adversarial Networks (GAN) have a substantial influence on the efficacy of MSA [15].

Consequently, the application of DL techniques—especially those from the field of artificial intelligence (AI)—has led to a steady increase in the use of multilingual tools in recent centuries. Translating the original text into English is one of the most frequently utilized strategies for accomplishing multilingual text classification [16]. The converted SA or text categorization. However, this method has shown that the sentiment of the data under examination has significantly decreased [17]. Using a sentiment lexicon that has been translated into several languages is an additional strategy. The primary disadvantages of this method are that human intervention is necessary during the text analysis process and that several lexical objects are not domain interoperable. As a result, Lexicon-based Analysis is continuing to establish in its earliest stages and optimization is still a work in progress [18]. Using annotated datasets remains a challenge for many languages with limited resources. Hence to overcome these drawbacks a novel framework is needed to analyze the sentiments in multilingual data.

The article's primary contribution is enumerated below:

- The SCEEAF-BiLSTM model is a new method for classifying multilingual sentiment in product reviews.
- Through a comprehensive preprocessing process, the model guarantees dependable input data preparation. In the meantime, the Semantic-ContextEmbed Extractor (SCEE) utilizes Skipgram and Continuous Bag-of-Words (CBoW) techniques to extract the optimal context and semantic information.
- Additionally, the model incorporates a Convolutional BiLSTM with Enhanced Attention (CoBLEA) architecture, utilizing attention mechanisms to capture significant word weights, convolutional layers for local high-level feature extraction, and BiLSTM for contextual information extraction.
- By incorporating these innovations, the model can overcome biases and inaccuracies introduced by prior methods and accurately classify the multilingual sentiments into positive, neutral, and negative states.

The remainder of the work is organized as Section 2 analyzes the prior work, section 3 designates the proposed method, section 4 reveals the outcome of the proposed method, and Section 5 completes the article.

2. Related work

SA has been widely researched across multiple domains, with various models and techniques proposed to address different challenges. Xu et al. [19] introduced a Continuous Naïve Bayes framework for massive sentiment analysis of product reviews in e-commerce platforms. The framework uses a continuous learning approach for parameter estimation, retaining high computational efficiency, and adjusting to different domains. However, the model's assumptions for domain adaptation may introduce bias in sentiment classification, especially when fine-tuning for various domains, as they may not fully capture the intricacies of the review contexts.

Onan et al. [20] proposed a deep learning-based SA technique for product reviews on Twitter, combining a CNN-LSTM structure and weighted GloVe word embeddings using TF-IDF. Although this method improved predictive performance, the informal language and character limit might introduce biases, limiting the model's applicability to more formal review platforms.

Sattar et al. [21] focused on sentiment classification for cross-lingual data using a multi-layer network with aspect-based attention. While their model leverages multilingual BERT and bilingual dictionaries for cross-lingual translation, the challenges in capturing mutual dependencies in multilingual data, and the lack of validation across various domains, limit its generalizability and effectiveness.

Mamta et al. [22] proposed a deep multi-task multilingual adversarial framework to address resource scarcity in SA by using cross-lingual word embeddings. However, the framework's inability to capture implicit sentiment in sentences highlights the need for semi-supervised techniques to enhance sentiment detection, especially in under-resourced languages.

Purohit et al. [23] introduced opinion mining techniques using Systemize Polarity Shift and Revival Extraction. While these methods aimed to categorize reviews and extract product aspects, decision-making challenges and the failure of unclassified SA limited their effectiveness in sentiment classification.

Liu et al. [24] suggested a DL-based SA approach that ranks products using Probabilistic Linguistic Terms (PLTSs). Although this approach demonstrated accurate prediction of sentiment levels from online product reviews, the challenge of detecting sarcasm remains unsolved, further hindering the model's ability to fully capture the nuances of review texts.

While these studies offer valuable insights into sentiment analysis, several limitations persist including due to its incapacity to fully capture the distinct characteristics of various review contexts, the model for sentiment classification in product reviews may introduce bias or inaccuracies. Limitations like validation across cross-lingual data domains, challenges in co-extraction of aspect-term and sentiment-polarity, and the requirement to add more implicit data using semi-supervised techniques across different languages may hinder the effectiveness and generalizability of the model. Classifying reviews and extracting product aspects is an ineffective use of opinion mining and SA techniques such as Systemize Polarity Shift and Revival Extraction. To overcome these drawbacks, there is a need to develop a novel framework for the analysis of sentiments.

3. Proposed methodology

The research proposed a Semantic-Context Embedding Enhanced Attention Fusion BiLSTM (SCEEAF-BiLSTM) for product review analysis in multilingual sentiments. The research effort aims to ensure generalizability, implicit sentiment detection refers to recognizing feelings determined from context, tone, or indirect language but not stated directly in the text, and adaptability across multiple domains and languages by addressing bias, and aspect-polarity classification issues. The preprocessing begins with tokenization, dividing the multilingual texts into smaller chunks. Term-based random sampling is then used in this research to remove all stop words from the text. The data is then cleansed by eliminating any occurrences of numbers in between words in a multilingual sentence, regardless of whether the numbers are written as symbols or words. At last, irrelevant components, like unused letters or symbols, are eliminated, and the review comments undergo lowercase normalization.ML models are case-sensitive, so case normalization is essential. Without it, words with the same meaning but different cases (upper or lower) could be interpreted as distinct, which could lower the classifier's efficiency. Subsequently, the best context and semantic information are extracted using the Semantic-ContextEmbed Extractor (SCEE) after the input data has been preprocessed. Combining the continuous Bag-of-Words (CBoW) and Skip-gram techniques, SCEE forecasts the word in the center of the window by using the central word as a predictor of the surrounding words, while CBoW extracts distributed representations of the context. Feature fusion is done before prediction because both the CBoW and Skip gram features are used to better represent each review comment and turn words into dense vectors, enhancing cross-lingual sentiment analysis by capturing semantic context more effectively. The research proposes a novel Convolutional BiLSTM with Enhanced Attention (CoBLEA) model for sentiment classification across multiple languages. It combines two attention layers, a convolutional neural network, and a BiLSTM. The BiLSTM extracts contextual information from the convolutional layer, extracting local high-level features and minimizing the feature set. The weights of significant multilingual words are used to extract context representation, which is then concatenated from the attention layers. The softmax activation function receives the output after that for classification. Figure 1 below represents the block diagram for the proposed method.

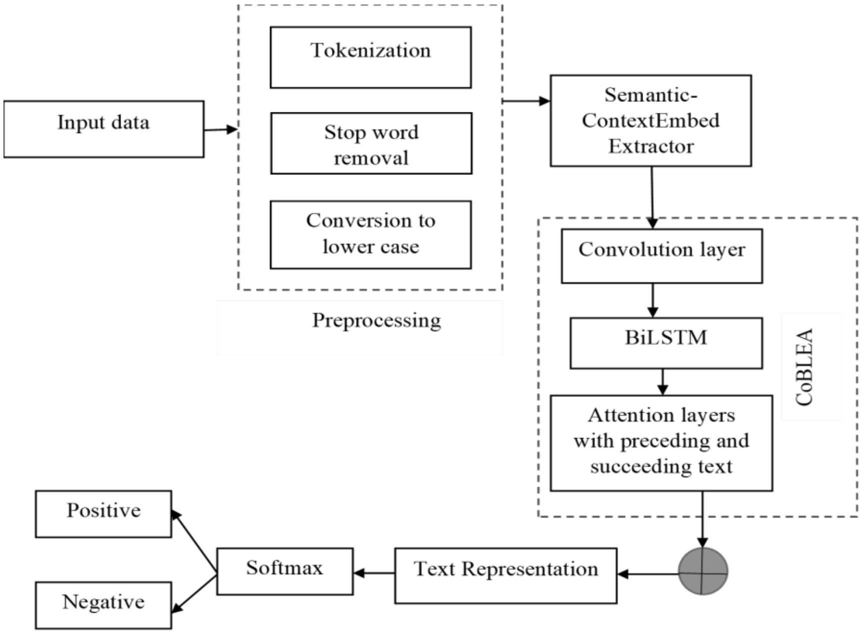

Figure 1. Block diagram for the proposed method

3.1. Preprocessing

Tokenization, stop word removal, and lowercase conversion are a few examples of multilingual text data preprocessing methods that are essential to getting the text ready for further analysis, such as MSA. The tokenization procedure of multilingual raw text involves separating it into discrete tokens, which are typically words or phrases that act as the basis for analysis. This technique divides the content into digestible parts so that the system can analyze and comprehend it correctly. Once tokenization is complete, stop word removal removes commonly used terms with low semantic value, like "the," "an", "is", and "and". By taking this step, noise is decreased and the accuracy of ensuing analyses is increased. Determining the stop words for various languages, the stop word list (customized or predefined), and the library or tool used (e.g., NLTK, spaCy) are all important details of the stop word removal process by eliminating these redundant terms. It also ensures uniformity in word representation across capitalization variations by converting all multilingual text to lowercase. By removing words that are capitalized differently from one another, this step increases the effectiveness of later tasks like MSA. Consequently, these methods enhance the quality of multilingual text data by mitigating issues like noise, unpredictability, and duplication, thereby facilitating more precise and effective MSA across an array of text data sources, such as reviews and comments. After that, the word embedding process will be shown below.

3.2. Semantic-ContextEmbed Extractor

By mapping individual words in a sentence to a 'v' vector, a technique known as word embedding allows multilingual words that have the representation of closely related semantic concepts in a hidden space. Compared to the bag-of-words approach, which conveys more sentence context in a low-dimensional space, this is a more sophisticated method. Neural networks require numerical data as input. Text vectorization is the process of converting multilingual text into a numerical representation. There are a few feasible text vectorization techniques. This is among the most widely used methods for word vectorization with neural networks. Google was the one who developed it. Word2Vec employs two techniques: CBOW and SkipGram structure are given in Figures 2 and 3 [28]. The word embedding architecture known as CBOW creates word embeddings by utilizing both past and future words. Equation (1) [27] provides the CBOW's objective function.

$$J_\theta = \frac{1}{T} = \sum_{t=1}^{T} log_p(c_t | c_{t-n}, \dots \dots, c_{t-1}, c_{t+1}, \dots \dots c_{t+n}) \tag{1}$$

The CBOW method predicts the word in the center of the window by using distributed representations of the context. Skip Gram forecasts the surrounding words by using the central word. Equation (2) [28] provides the Skip Gram's objective function.

$$J_\theta = \frac{1}{T} = \sum_{t=1}^{T} \sum_{-n \leq j \leq n, \neq 0} log_p(c_{j+1} | c_t) \tag{2}$$

The log probabilities of the n words immediately to the left and right of the target word, c_t are added together to determine the primary purpose of the Skip Gram, as given by Eq. (2).

The embedding's parameters are: the smallest quantity of a word that must appear in the corpus for it to be incorporated into the model is known as its size.

Window: The maximum gap in a sentence between the actual and anticipated words. Workers: It indicates the number of parallelization threads that are currently operating for quicker training.

min_count: Specifies the minimum number of occurrences required for a word to be included in the feature vectors' dimensions.

SG: CBOW is carried out if its value is zero; otherwise, Skip Gram is carried out. The prediction will be discussed in the below section.

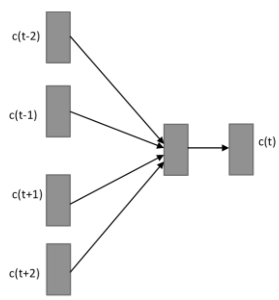

Figure 2. CBOW structure

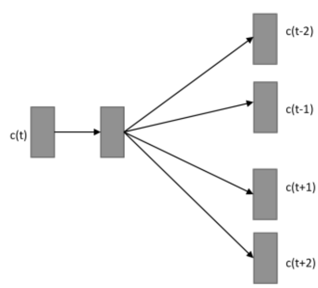

Figure 3. Skip-gram Structure

3.3. CoBLEA model

CoBLEA predicts multilingual sentiment by combining two attention layers with a convolutional neural network and a BiLSTM. Using features retrieved by each forward and backward hidden layer's convolutional layer, BiLSTM can extract contextual information as sequences. The convolutional layer is utilized to extract the local high-level features, and a max pooling layer minimizes the feature set. The weights of the significant words are used to extract context representation through the application of two attention layers. The BiLSTM contextual information sequences provide these representations that come before and after. To create a thorough context representation, the contextual data that was obtained from the attention layers is additionally concatenated. Lastly, the output is sent to the softmax activation function, which divides it into two classes: positive and negative. The Architecture of CoBLEA is shown in Figure 4 and the overall functioning of each layer is summarized below.

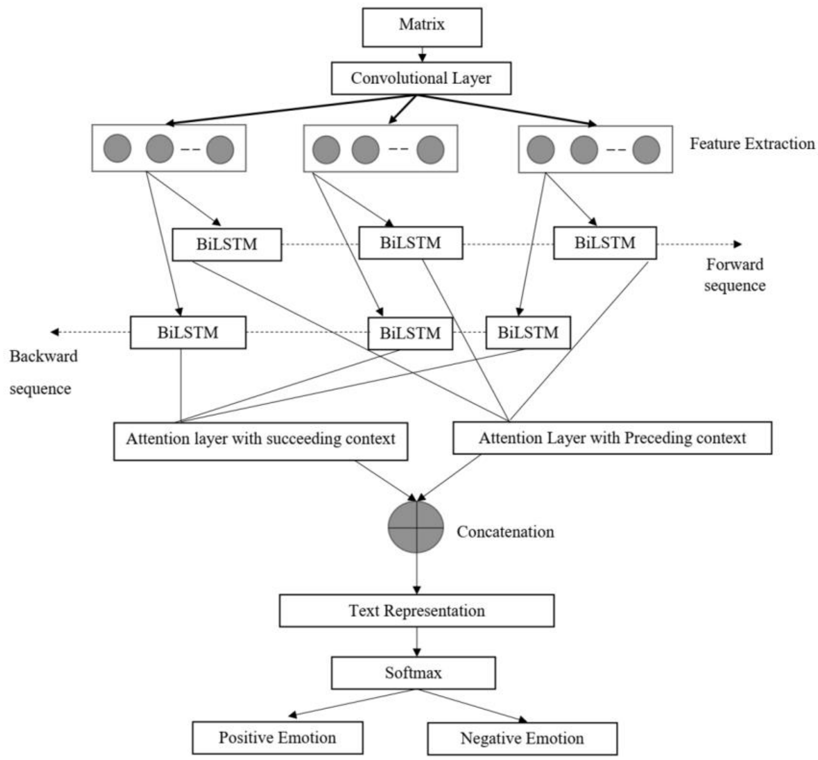

Figure 4. Architecture of the CoBLEA

3.3.1. Convolution layer

The input layer of the word embedding, created with various vector dimensions, was the first layer. The convolutional network receives its input from the matrix results. CNN was used, among other things, to learn how to classify multilingual texts that were encoded as a series of embeddings. From the convolutional layer, obtaining the input matrix's most essential regional features. With L2 regularizers and ReLU activation, the conv1d layer contains 64 filters each of the size 3.

To downsample the input, a max pooling layer is employed, and both the pool size and the strides are set to 2. Accepting the review text vector $a_i^0 = a_1, a_2, a_3, a_4, a_5, \dots \dots, a_n$ produced the input representation layer, the input layer uses the output of the convolutional layers to perform a convolution operation to precisely retrieve the sentiment information locally contained in the multilingual review text, as shown in Eq. (3). The convolutional kernel weight is denoted by the symbol w, and the bias mapped by feature j is represented by the term b_j^l. σ Stands for the ReLU activation function, and m for the filter index. The pooling stride is represented by $R\ and\ T$, MV_w represents the matrix vector respectively. The eq. (4) [27] is shown below.

$$MV_w = A_1, A_2, \ldots \ldots, A_n, A_{n+1} \tag{3}$$

$$v_{ij}^I = \sigma\left(\sum_{m=1}^{M} w_{m,j}^I a_{i+m-1,j}^{I-1} + b_j^I\right) \tag{4}$$

The pooling layer receives the review text after the convolution procedure to additionally minimize the number of factors, the dimensionality of the data, and the local sentiment data is given as eq.(5) [29].

$$a_{hidden} = \max_{r\epsilon R} v_{i\times T+R,j}^{I-1} \tag{5}$$

3.3.2. Bidirectional Long Short-Term Memory (BiLSTM)

Information about the past is obtained using a forward LSTM state, and information about the future is obtained using a backward LSTM state. The network can recall past events and future developments more easily with this kind of organization. Any neural network can store a sequence of inputs in both forward and backward directions using the BiLSTM technique. This is different from a standard LSTM in that inputs can flow in both directions. The output layer simultaneously gathers data from the preceding sequences (backward) and the subsequent sequences (forwards). Final result h: following the stacking of Bi-LSTM layers. While backward LSTM state is employed to gather information about the future, forward LSTM state is utilized to gather information about the past. The network can remember what came before and what will come after because of the way it is configured. Bi-LSTM operates by feeding the first layer's sequence output into the second layer, whose sequence output is the sum of the front and backward layers' final unit outputs. h is the outcome of multiple Bi-LSTM layers is given as Eq. (6) [27].

$$h = h_{forward}, h_{backward} \tag{6}$$

As a result, it is quite helpful when the input multilingual context is needed, like when a positive term comes after a negation term.

3.3.3. Attention layer

Through the application of weights to individual words in a multilingual text, NNs' keywords are highlighted by the attention mechanism while reducing the impact of non-keywords. This study makes use of two attention layers to allow terms in a review to have varying weights, which enhances word/token comprehension. By emphasizing self-critical sarcastic keywords, the attention mechanism increases their significance and decreases the impact of non-keywords in multilingual review data. First, a single-layer perceptron is utilized to extract a hidden depiction $\overrightarrow{\delta_f}$ using the word annotation $\overrightarrow{h_f}$. This procedure, which is formally expressed in equation (7) [27], creates the hidden representation by utilizing the hyperbolic tangent function $tanh$, the weight ω and bias b parameters.

$$\overrightarrow{\delta_f} = \tanh\left(\omega \overrightarrow{h_f} + b\right) \tag{7}$$

Using multilingual word-level context vectors $\overrightarrow{\delta_f}$ and $\overrightarrow{\vartheta_f}$, the proposed model compares the similarity between words. Despite being entirely trained, this vector $\overrightarrow{\vartheta_f}$ is randomly generated and offers a thorough representation of self-deprecating sarcastic terms from multilingual reviews. The softmax activation function is utilized by the model to determine a normalized weight $\overrightarrow{\sigma_f}$ for every word given as Eq. (8) [27]

$$\overrightarrow{\sigma_f} = \frac{e^{(\overrightarrow{\delta_f} * \overrightarrow{\vartheta_f})}}{\sum_{i=1}^{N} e^{(\overrightarrow{\delta_f} * \overrightarrow{\vartheta_f})}} \tag{8}$$

Utilizing $\overrightarrow{h_f}$ and $\overrightarrow{\sigma_f}$, respectively, as well as the weighted sum of word annotations $\overleftarrow{h_f}$ and normalized weight $\overleftarrow{\sigma_f}$ in the backward direction, equations (9) and (10) [27] calculate the context representations that are forward and backward, respectively. By incorporating the context representations for the forward and backward directions F_c and B_c, one can obtain the annotation of a feature sequence Q_f. A collection of all-inclusive features is represented by $S_c = [F_c, B_c]$. This is fed into a two-class LR function called the softmax activation function, which determines whether multilingual review data contains positive or negative emotions.

$$F_c = \sum(\overrightarrow{\sigma_f} * \overrightarrow{h_f}) \tag{9}$$

$$B_c = \sum(\overleftarrow{\sigma_b} * \overleftarrow{h_b}) \tag{10}$$

The obtained document feature is sent to the layer of softmax following concatenation. Let's use Eq. (11) [27] to represent the final data feature z.

$$z = Concat\ (\lambda z_c, (1-\lambda) z_w), \lambda \in [0,1] \tag{11}$$

Identifying the feature matrix input is this layer's main objective. For every feature, an integer in the range of 0 to 1 has been given in this layer. The input text grows increasingly negative and sentimental as the relevance comes near to zero. A value that is closer to one is thought to represent the input text and suggests that the multilingual sentiment's polarity is more skewed towards the positive. The outcome of the proposed method will be discussed below.

4. Results and discussion

A comparison of baselines and detailed descriptions of the assessment metrics, outcomes, and datasets are provided in the following section. The ensuing subsections are explained upon each of these constituents to offer a thorough comprehension of the outcomes. The Python programming language is used for implementation with tensor flow libraries.

4.1. Dataset Description

An initial dataset of Amazon reviews was created especially to support investigation in tasks for classifying texts in multiple languages, and it served as the basis for training and assessing the introduced models. English, Japanese, German, French, Chinese, and Spanish reviews are included in the dataset. Reviews were gathered between November 1, 2015, and November 1, 2019. A concealed "review ID," a concealed "product ID," a concealed "reviewer ID," the review text as "review_body," the review title as "review_title," the star rating as "stars" feature, the "language" that serves as the basis for the review, and the coarse-grained "product category," such as "furniture," "sports," etc. are all included in each record represented into the various language datasets. Additionally, the database is evenly distributed across a 5-star rating system (1 being "highly negative" − 5 being "highly positive"), meaning that 20% of the reviews in each language are represented by each star. There are 200,000, 5000, and 5000 reviews for each of the five languages under examination in the training, enlargement, and test sets, correspondingly. There can be a maximum of 20 reviews for each reviewer and up to 20 reviews for each product. Every review is at least 20 characters long and is truncated after 2000 characters. It is also important to highlight that there are 31 distinct product categories included in the various language datasets, each of which has a different distribution and frequency of occurrence. This multilingual dataset was used to train and test the proposed models to assess their effectiveness in terms of both the 5-star rating system on Amazon serves as the basis for the multilingual SA mission, the sentiment of the reviews, and the identified class in terms of the task of categorizing multilingual texts. Training and testing versions of the dataset were separated as, 80% used for training and 20% used for testing.

The technique was trained using Adam optimizer with verbose 2 batch size 128, learning rate as 0.001, and binary cross entropy loss function considering their suitability for classifying the sentiments as positive and negative for 100epochs.

4.2. Metrics Used

Four standard metrics are employed to assess the proposed model: accuracy, recall, f-score, and precision given as eqs. (12) -(15) [30]. These measurements are specified in terms of False Positive, True Negative, False Positive, and False Negative. The amount of correctly identified sentiment reviews is the expression for TP. FP is the number of incorrectly identified. The number of accurately detected is represented by TN. FN is finally described as the quantity of falsely recognized reviews.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

$$F1 - Score = 2 \times \frac{Pecision \times Recall}{Precision+Recall} \quad (15)$$

4.3. Results for Performance Evaluation

The result for accuracy and loss was evaluated by the proposed SCEEAF-BiLSTM model.

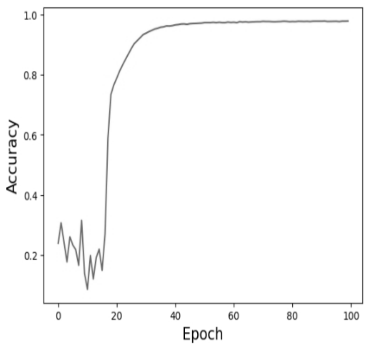

Figure 5. Accuracy vs Epochs

Figure 5 indicates the proposed method's accuracy graph. When the SCEEAF-BiLSTM model was optimized using the Adam optimizer, it showed remarkable performance in identifying complex patterns in the data. Its ability to shift quickly through the optimization landscape was facilitated by its advanced architecture and adaptive learning rate mechanisms. The accuracy graph shows the model's potential for high-performance sequential data analysis applications by showcasing its capacity to represent intricate dependencies and produce accurate predictions. The proposed model accuracy attained 98.7%, after the 40 epochs it remains constant.

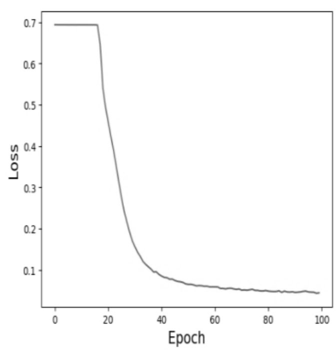

Figure 6. Loss vs Epochs

The loss graph for the proposed technique is presented in Figure 6. According to the graph, the proposed model made use of the cross entropy loss, which obtained 0.7 for 20 epochs after that it rapidly decreased to 0.1 for after 25th epochs then it slowly decreased to obtain 0.08 for up to 100 epochs.

4.4. Comparison

To compare the metrics such as accuracy, precision, recall, and F1-Score of the proposed technique with prevailing methods including Bidirectional Encoder Representations from Transformers (BERT) [25], CNN [25], BERT-CNN [26] and BERT-MultiLayered CNN (BMLCNN) [26].

Model	Accuracy	Precision	Recall	F1-Score
BERT	0.91	0.89	0.91	0.90
CNN	0.89	0.89	0.91	0.90
BERT-CNN	0.91	0.88	0.91	0.90
BMLCNN	0.95	0.94	0.94	0.93
Proposed CoBLEA	0.987	0.985	0.978	0.986

Table 1. Comparing the Performance of the proposed method

Table 1 provides a comparison of the suggested technique's performance with existing models. The proposed model achieves an impressive accuracy of 0.987 and a near-perfect F1-Score of 0.986, clearly outperforming the traditional models (BERT, CNN, BERT-CNN, and BMLCNN) across all performance metrics. This indicates that the proposed method offers significant improvements over existing methods in handling complex multilingual sentiment analysis tasks. It also shows that the model is more effective at capturing both precision and recall.

4.5. Discussion

With notable improvements over existing ones such as BERT, CNN, BERT-CNN, and BMLCNN, the proposed model presents a novel approach for MSA. The distinctive architecture of the model, which combines SCEEAF-BiLSTM, is responsible for this performance improvement. The model differs from other approaches in that it can capture the complex, context-specific meanings found in multilingual data while resolving issues with polysemy and homography. The attention mechanism of the suggested method, which improves the model's focus on pertinent information across languages, is one of its key innovations. This enables the model, independent of linguistic variances, to more accurately interpret the sentiment expressed in reviews. Convolutional and BiLSTM layers enable the model to capture both sequential and local patterns, which makes it ideal for analyzing complex text structures found in multilingual datasets. The proposed framework minimizes false positives and false negatives by carefully balancing precision and recall in addition to accurately identifying sentiment. In contrast to prevailing models the proposed model outperforms better than other models and accurately classifies the classes of multilingual sentiments such as positive and negative. The effectiveness of the SCEEAF-BiLSTM model in MSA is demonstrated by such results, surpassing existing state-of-the-art methods and highlighting its potential for accurate and comprehensive textual analysis tasks. The SCEEAF-BiLSTM model's total complexity is $O(V.d.C) + O(k.T.F) + O(2.h.T) + O(T^2.h)$ where the largest contributions to computational cost are provided by the vocabulary size V, sequence length T, k is the filter size, F is the number of filters and attention mechanism. For longer sequences, the main source of complexity is the quadratic term $O(T^2.h)$ in the attention layer where h is the number of BiLSTM hidden units. Despite the success of the SCEEAF-BiLSTM model, several drawbacks warrant further investigation. One limitation is its difficulty in handling low-resource languages, where data scarcity can hinder performance. Additionally, the model's generalizability across different domains is limited, which may affect its ability to adapt to diverse datasets. The model's reliance on resource-intensive training can also pose challenges in terms of scalability and efficiency. Furthermore, the model may struggle with ambiguous sentiment polarity and potential bias present in the training set. To address these issues, future work should focus on incorporating more advanced NLP techniques, such as transformer-based models, to enhance MSA accuracy. These models could help improve the framework's ability to capture subtle semantic variations across languages and domains, ensuring a more robust and adaptable solution for real-world applications.

5. Conclusion

In conclusion, the comprehensive SCEEAF-BiLSTM technique for MSA of product reviews was presented in this work. Utilizing methodical preprocessing procedures such as tokenization, removal of stop words, and case normalization, the input data is prepared for efficient analysis. By combining CBoW and Skipgram techniques, the SCEE was instrumental in obtaining the best possible context and semantic information from the reviews. The representation of each review comment is then improved by fusing this data. By combining convolutional, BiLSTM, and attention mechanisms, the CoBLEA model was developed to further improve this representation. Using contextual data, attention-weighted representations, and local high-level features, the model achieved robust sentiment classification into positive, neutral, and negative categories. All things taken into account, the SCEEAF-BiLSTM framework provides an advanced method for MSA in product reviews, showing great promise for uses requiring subtle comprehension of textual data. Specifically, the proposed method revealed the outcomes of accuracy attained 0.987, precision attained 0.985, recall attained 0.978 and F1-Score attained 0.986 when compared to the baseline of the works.

Conflict Of Interest

There is no conflict of interest, according to the writer's statement.

Ethical Approval

Approval from the Institutional Review Board was not necessary.

Consent for Participate

Every contributor gave their approval and consent to take part.

Consent for Publication

Permission to publish was granted by each contributor.

Data availability

Models, information, or code were not developed or utilized for the study's objectives.

Competing interests

None

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Author Contribution

The following contributions to the paper are confirmed by the authors, who have all reviewed the findings and given their approval to the manuscript's final draft.

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Fueling the Innovation Spark: How Employee Oriented HR Practices and Career Satisfaction Fosters Innovative Work Behavior?

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ABSTRACT

Employee-oriented HR practices have ascertained their instrumentality in nurturing innovative work behavior (IWB) of employees via career satisfaction (CS). This study aims to investigate how employee-oriented human resource (HR) practices (salary, job enrichment, job stability, training) can influence career satisfaction that subsequently affects employees' innovative behavior. Anchoring on social exchange theory and signaling theory, the data for the study was collected from 358 employees of Small and Medium Enterprises (SMEs) by purposive sampling. The study applied Structural Equation Modeling (SEM) using SmartPLS 4 to test the proposed hypotheses. The findings of this study offer useful insights into the degree to which career satisfaction mediates the impact of employee-oriented HR practices on innovative work behavior. The results suggest a significant but moderate to weak; positive association between employee-oriented HR practices and their innovative activity. Furthermore, the research establishes the mediating impact of career satisfaction while investigating the mechanism through which employee-oriented HR practices foster innovative work behavior. The study expands the knowledge base of extant literature by illuminating the critical role of employee-oriented HR practices in driving employees' innovative behavior at the workplace. Besides, it illuminates the mediating role of career satisfaction, accenting the necessity for companies to not only implement employee-oriented HR practices but also foster a sense of satisfaction within employees to unearth the full potential of innovative behaviors within the workforce.

Keywords: Employee Oriented HR Practices, Career Satisfaction, Innovative Work Behavior

1. Introduction

Research into the connection between human resource practices and organizational outcomes has spanned four decades, though substantial empirical evidence did not emerge until the 1980s [1], [2]. Innovative work behavior (IWB) is fundamental element of organizational innovation [3] as numerous researchers assert its significance in achieving corporate success [4]. Research into the connection between human resource practices and organizational outcomes has spanned four decades, though substantial empirical evidence did not emerge until the 1980s [1], [2]. It increases the prospect of organizational innovation, strengthens the relationship between the organization and employees, and improves the competitiveness and performance of the firm [5]. Additionally, there is increased interest among HR professionals in positive psychology, which emphasizes employee well-being, happiness, and productive thoughts like employee dedication as a path to individual efficiency [6].

Accordingly, a greater part of scholarly attention in innovation management literature has been attracted by innovative work behavior [7]. The research of earlier scholars profess that leadership [8], the climate of creativity [9] serving as external factors and individual mood and personality [10], self-efficacy [11], serving as internal contextual factors; can be vital in architecting innovative behavior of workers. Nevertheless, inconclusive evidence is available regarding the importance of HR practices in defining the innovative behavior of employees at workplace [12]. Past studies establishes the instrumentality of employee-oriented HR practices [13] as much of the research, conducted till date, is limited to the organizational-level outcomes thereby calling for investigation into employee-level outcomes [14].

Despite the growing research on innovative work behavior on one hand [15] and HR practices on the other hand [16], our knowledge about the relationship between the two has slowly developed [17]. Earlier studies ascertain the instrumentality of HR practices in employee innovation [18], yet the mechanism of influencing the innovative behavior of employees via such practices needs further investigation [17], [19]. In addition, scholars not only have recommended using psychological mediators, such as career satisfaction, [20] but also how career satisfaction may influence job related outcomes of the employees [21]. To fill this gap, the present study attempts to examine the mediating role of career satisfaction in investigating the influence of employee-oriented HR practices on employees' innovative behavior at workplace. There has been a dearth of research on the innovative behavior of employees in small and medium-sized firms (SMEs), with the majority of studies focusing on large scale enterprises (LSEs). Based on financial and capability constraints, SMEs are reluctant to adopt the strategies to innovate rather bracing their innovative capabilities by relying on external sources [22]. The SMEs' incapacity to innovate independently has an even greater impact on how they adopt innovation, which drastically influences their performance in case of industrial turbulence [23]. Therefore, there is a need to investigate how employees' innovative behavior is self-triggered in the context of SMEs [24]. Accordingly this research drawing on social exchange theory [25] and signaling theory [26] ascertain the role of employee oriented HR practices impact on career satisfaction that consequently foster employee innovative behavior.

This research provides several contributions by studying the influence of employee-oriented human resource practices on employee innovative behavior. First, we link employee-oriented HR practices, including job enrichment, salary, job stability and job training with nurturing of employee career satisfaction. Such association is vital given that employee motivation challenges at work are gaining scholarly attention in management and behavioral psychology literature, and that HR practices must foster innovative behavior in workers by enhancing their psychological and human resources capabilities [27]. Second, this research extends the theoretical framework in human resources management, specifically through the lens of positive psychology, to empirically investigate whether or how employee-oriented HR practices can be utilized as a strategic tool to foster innovative work behavior by establishing a "win-win situation". Third, the originality of the present study rests in the conceptualization of career satisfaction as a developable phenomenon that can be influenced by a specific bundle of HR practices. As a result, the study advances knowledge of the multi-staged processes by which employee-oriented HR practices can promote career satisfaction which can be instrumental in the development of innovative work behavior. Finally, this research would add to social exchange theory and signaling theory illuminating the role of employee-oriented HR practices in shaping workplace satisfaction and employee innovative behavior.

2. Theoretical Background

2.1. Employee-Oriented Human Resource Practices

The concept of employee-oriented human resource (HR) practices refers to the advocacy of investments in human resource through training and development opportunities while also providing a meaningful work experience that covers elements such as humanly possible workloads, defined roles, employee autonomy, transparent communication, and promoting a positive organizational culture characterized by employment stability and teamwork, as well as enabling employee representation through two-way communication [28]. Human resource practices play are instrumental in development of employees' skills, competency, and behavior, subsequently enhancing their creativity and innovative thinking [29]. Similarly, Aragon & Jimenez-Jimenez [30] professed the interconnectedness of human resources and innovation process thereby acting as an influential factor in enhancing innovation at workplace. Salary, as one of the dimensions of HR practices, was found to have a positive influence on innovation performance. Pan et al., [31] in their work ascertain the influence of salary gap on enterprise innovation. Furthermore, job enrichment [32], job stability [33], and job training [16] were also found to have a positive impact on innovative behaviors of employees.

Majority of the studies investigating the impact of HR practices on employee performance neglected the role of employee well-being [34]. Therefore, an alternate technique that significantly improves employee well-being is required to provide a substitute for employee performance. Yet, the explanation of how HR practices fosters employee well-being and psychology by scholars and practitioners remain limited [13].The substantial influence of positive psychology on determining employee attitudes and behaviors makes this discussion highly relevant in behavioral research [35].

2.2. Career Satisfaction

In last decade, career satisfaction (CS) has attained much scholarly interest [36] because of its significance in organizational behavior literature particularly determining the dynamics between work environment and job performance [37]. Career satisfaction refers to individual's feelings regarding the accomplishment of their career specific goals and their level of contentment in fulfillment [38].

Although there is a growing interest among scholars regarding career satisfaction literature, limited understanding has so far been developed and calls for further investigation [39]. For example, Oubibi et al., [40] investigated the mediating impact of work engagement and job crafting while studying how perceived organizational support influences career satisfaction. Similarly, Salleh et al., [41] examined how career satisfaction serves as a mediating mechanism while investigating the role of career planning in employees turnover intention. However, Islam and Ahmed, [21] has asked for further investigation of how career satisfaction may influence employees' job-related outcomes.

2.3. Innovative Work Behavior

Innovative work behavior (IWB) denotes the voluntary measures undertaken by individuals to enhance organizational performance and surpass role expectations [42]. Such behavior plays a significant role in organizational competitiveness and innovation. It signifies individual initiatives aimed at generating, developing, and executing innovative concepts to improve organizational performance, encompassing procedures, products, technology, and work processes. [43]. Innovative work behavior is considered a critical phenomenon resulting in increasing scholarly interest in organizational studies. IWB has ascertained its vitality for the firms to achieve competitive advantage [44], and superior performance [12]. While existing research confirms the importance of innovative work behavior (IWB) for achieving competitive advantage [45], there is a paucity of information regarding the methods to motivate employees to exhibit innovative behavior within businesses [16]. Since the vitality of employees in shaping the organization's potential for innovation cannot be ignored [46], scholars profess the investigation of certain HR practices that may foster innovative behavior [27]. Shin et al., [47] argued that the managerial staff is not completely responsible for innovation. Besides, the employees working at the operational level contribute equally to the initiation and implementation of new business ideas [48]. Recent studies on the workers' involvement in innovation process suggest that, if smartly invested, employees can display innovative behavior [12]. Consequently, there is a dearth of studies identifying the bundle of HR policies that can promote innovative behavior among employees.

3. Hypotheses development

The fundamental ideology of the proposed model (see Figure 1) professes the multi-dimensional impact of employee-oriented HR practices on innovative work behavior via career satisfaction. Drawing on social exchange theory [25] and signaling theory [26] as theoretical anchors for understanding the proposed model, this research investigate how employee-oriented HR practices impact the innovative work behavior of employees via career satisfaction. Social exchange theory posits that employees who see their organization as valuing them are likely to respond with positive behaviors. [49]. If HR practices are implemented by an organization that values employees, they will contribute constructively to the company. Furthermore, signaling theory posits that employee-focused HR practices demonstrate the company's ongoing commitment to its staff, enhancing contentment and promoting reciprocal innovative activity among employees. [50].

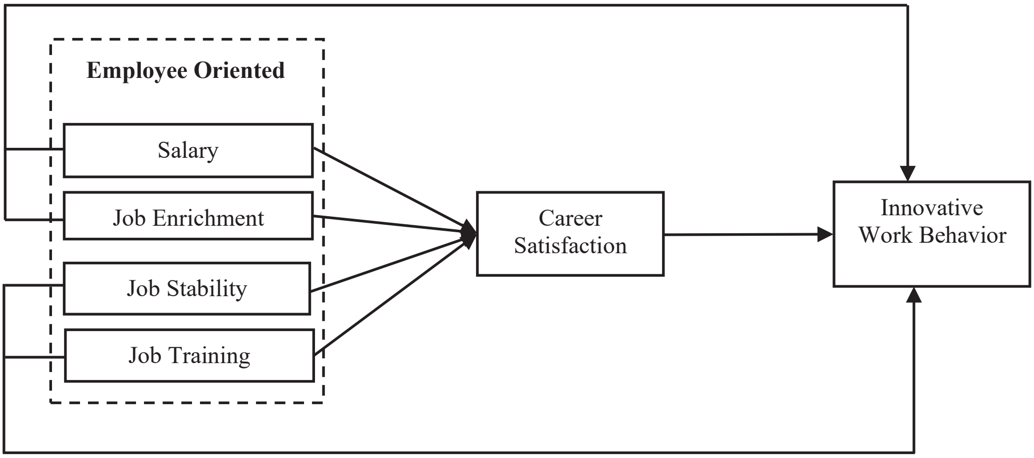

Figure 1. Proposed Research Model

The intended behavior of employees can be promoted by the firms by the implementation of HR practices that nurture a particular behavior and actions while discouraging undesirable behaviors. The HR practices plays a pivotal role in the enhancement of employees competence and fosters innovative behavior [12]. Investment in employees is considered to enable greater obligation by individuals towards the company [51]. Drawing upon social exchange theory, grounding in the principles of reciprocity, this research proposes that if a company introduces employee-oriented HR practices, employees will make a valuable contribution as a repayment to the investment made by the organization [52]. Moreover, extant research revealed that salaries, job stability, job enrichment [35] and job training [27] are significantly associated with innovative work behavior and better job performance. Thus, employee-oriented HR practices build a positive perception of organization's seriousness towards employee development [53] that affects their innovative behavior [54]. Extant studies highlighted the impact of HR practices on innovative behavior of employees, yet, the identification of specific HR bundles that promotes innovative work behavior remains inexhaustive [12]. Therefore, the study posits the following hypotheses:

H1a: Salary is positively associated with innovative work behavior.

H1b: Job enrichment is positively associated with innovative work behavior.

H1c: Job stability is positively associated with innovative work behavior.

H1d: Training has a positive impact on innovative work behavior.

Career satisfaction has increasingly been recognized as an important variable in organizational psychology due to its significance in achieving organizational goals and objectives [55]. This phenomenon pertains to the factor that establishes a connection between employees and the firm [56], subsequently playing a pivotal role in augmenting the overall success trajectory of the organization [57]. Previous research has shown that employee-oriented HR promotes an enduring social exchange relationship, which enhances employees' satisfaction at their job. [58]. The presence of employee-oriented HR practices cultivates a feeling of care among the employees and a sense of ownership by the company; consequently fostering the feeling of satisfaction toward the firm [59]. This research has used signaling theory as a theoretical anchor to understand the relationship between the constructs. Signaling theory has emerged as a compelling framework for comprehending the ramifications of HR practices oriented towards employees, specifically concerning their effect on fostering career satisfaction [60]. According to the theory, employee-focused HR practices are perceived by employees as a sign of long-term investment in workers, which drives them to repay by performing better in the company [61]. Despite the growing interest, previous studies focused on the firm-level impact of HR practice while the individual-level impacts remain inconclusive [14]. Thus, there is a need for a more holistic understanding of how employee-related HR practices might influence the career satisfaction of employees in the workplace. Hence, based on the above arguments, this research aims at testing the following hypotheses:

H2a: Salary positively and significantly influences career satisfaction.

H2b: Job enrichment significantly and positively influences career satisfaction.

H2c: Job stability significantly and positively influences career satisfaction.

H2d: Training significantly and positively influences career satisfaction.

In recent years, the career satisfaction of employees has garnered scholarly interest within the domain of employee attitudes and behavior. [62]. It refers to a positive psychological mindset developed by employee from outer and inners aspects of the profession [63]. It relates not just to employees' evaluation of the current working environment but also to their satisfaction with job prospects, chances for promotion, and overall work vitality [64]. Career satisfaction is mostly professed to be a consequent of the assessment of one's own success in the workplace, the accomplishment of career goals, and anticipation of future development [38].

Drawing on social exchange theory, the provision of job related benefits is instrumental in fostering individual’s job satisfaction; resulting in a positive and valuable response, such as exhibition of positive work behavior [65]. Extant research has associated career satisfaction with employees’ workplace loyalty and engagement, superior performance, and lower employee turnover [66]. Moreover, it has also been found to motivate individuals to shape innovative behavior. Employees may be encouraged for generation, sharing, promotion, and implementation of innovative ideas highly driven for ensuring success and safety of their careers [67]. Having positive emotional states linked to career satisfaction facilitates the development of creative resources and helps individuals to be resilient to setbacks, like unsuccessful innovation attempts [66]. It is assumed that workers having high careers satisfaction are more inclined to exhibit reactiveness at work, display highly innovative behavior, and resilience from failures. Thus, the study proposed the following hypothesis:

H3: Career satisfaction positively associated with innovative work behavior.

3.1. The mediating role of career satisfaction

In HR literature, there has been a significant increase in interest in determining the antecedents of employees' perceptions of their career prospects in organization [68]. Extant literature suggests that employee-oriented HR practices are instrumental in establishing the role of career satisfaction of employees [21]. Similarly, Kundi et al., [62] professed that employees will experience greater career satisfaction upon receiving support from their organizations in the form of discretionary HR practices, in turn, will result in greater association with their organization. Doing so, career satisfaction mediates the impact of employee-oriented HR practices and innovative work behavior. Making signaling theory as a theoretical base, the research recommend that the signals of concern for employees’ career sent by the organization are reciprocated by employees with high-level discretionary behavior like IWB [16]. Numerous studies focused on how HR practices affect firm-level innovation, but less is known about how they affect individual innovation [16], [21]. Hence, this research put forth the hypotheses as below:

H4a: Career satisfaction mediates the relationship between salary and innovative work behavior.

H4b: Career satisfaction mediates the relationship between job enrichment and innovative work behavior.

H4c: Career satisfaction mediates the relationship between job stability and innovative work behavior.

H4d: Career satisfaction mediates the relationship between training and innovative work behavior.

4. Research Methodology

4.1. Research Design

This study chose positivism as a relevant research philosophy, as it attempts to predict the impact of employee-oriented HR practices on employee innovative behavior via deductive reasoning. The quantitative approach is deemed suitable for the study due to the availability of extensive literature on the understudied phenomenon [13], [27], [69], which supports the formulation of a conceptual model and hypothesis testing [70].

4.2. Context and Participant of the Research

Data was collected from employees of Small and Medium Enterprises (SMEs) for their significant contributions to the development of national, industrial, and social growth strategies, as well as job creation [71]. In Pakistan, small and medium-sized enterprises (SMEs) account for nearly 90% of all business operations [72]. Despite such a huge presence and human capital's vital role in sustaining competitive advantage [73], the relevant literature in the context of small and medium enterprises (SMEs) needs further investigation [71]. investigation [71]. This study proposes that small and medium enterprises serve as an appropriate context for investigating the role of employee-oriented HR practices in the innovative behavior of employees at work, to address the issues in theory, research, and practices that arise as a result of the scarcity of information about HR in SMEs [74].

This study employed a purposive sampling strategy through direct interaction with the research participants. The research participants, prior to providing questionnaires for carrying out the survey, were provided with consent forms and information sheets describing the objectives of the research. Out of 400 questionnaires distributed among the employees, we received 374 with a response ratio of 93.5 %. Out of which, 16 surveys were eliminated due to errors, inadequacy, incompleteness, and missing values. Consequently, a sample of 358 questionnaires obtained with 89.5% response rate was utilized in data analysis.

4.3. Construct Measures

In order to develop the questionnaire, this research adapted the pre-established scale of past studies. Unless otherwise stated, every question was weighed on a Likert scale of 1 (strongly disagree) to 5 (strongly agree) on a five-point scale.

4.3.1. Salary (Sal)

A three items scale was adapted for measuring the salary on a five-point Likert-scale developed by [75] ranging from totally unsatisfied =1 to totally satisfied =5. A sample item included “I am satisfied with my pay in comparison to the employee in similar positions at rival companies.” Cronbach’s $\alpha = 0.721$.

4.3.2. Job Enrichment (JE)

A three-item scale was used for assessing job enrichment from Hackman and Oldham's [76] Job Diagnostic Survey with some adaptations. A sample question includes: “I have to use a range of your abilities and skills to accomplish a number of tasks as part of my job.” Cronbach’s $\alpha = 0.894$.

4.3.3. Job Stability (JS)

A two items scale for measuring job stability was adapted from the Job Diagnostic Survey of Hackman and Oldham [76]. Items include: “If I perform well in my job, my company will not terminate me”. Cronbach’s $\alpha = 0.882$.

4.3.4. Job Training (JT)

A four-item scale of Venkatesh et al., [77] was adopted to assess the overall training program. Such as, “Overall, I am satisfied with the training provided in this company”. Cronbach’s $\alpha = 0.821$.

4.3.5. Career Satisfaction (CS)

A five-item scale was adapted from [78] for measuring career satisfaction. For example, “I am happy with the professional accomplishments I have attained.” Cronbach’s $\alpha = 0.802$.

4.3.6. Innovative Work Behavior (IWB)

For measuring innovative work behavior, a six-item scale was adapted from the work of Scott and Bruce [79]. A sample item includes, “The employees in my organization search out new technologies, processes, techniques, and/or product ideas”. Cronbach’s $\alpha = 0.863$.

4.3.7. Control Variables

Prior studies indicated a relationship between demographics and innovative work behavior [80]. The present study, therefore, controlled the demographic variables including age, gender, education and experience. In specific, this research used the following codes for the control variables: employees age (20-30 years = 1, 31-40 = 2, 41-50 = 3, 51-60 = 4), employee gender (male = 1, female = 2), employee qualification (bachelors = 1, masters = 2, PhD = 3) and employee experience (1-10 years = 1, 11-20 years = 2, 21-30 years = 3).

4.4. Non-response bias

The non-response bias was checked as recommended by Armstrong & Overton [81] for assessing the likelihood of non-response bias. The study performed a t-test comparing the dataset of the initial fifty participants with that of the final fifty participants. The t-test results indicated that no significant variance ($p < 0.05$) was observed amongst the two groups. Hence, the t-test confirms that the study's results are not likely to be significantly influenced by non-response bias.

4.5. Sample Characteristics

In the 358 responses received, 252 were male and 106 were female, constituting 70% and 30% of the entire sample, correspondingly (Table 1). Majority of the research participants were between the age of 21 to 30 (43%) while 41 people under the age of 41-50 represented the lowest group in the sample. On the other hand, 117people aged from 31 to 40 (33%) while 46 people belong to the age group of 20 years and below (13%). In terms of educational background, more than half of the participants (75%) hold an undergraduate degree while respondents with intermediate certificate was 5%. Similarly, graduate students or above represented 20% of the total sample. Analysis of participants' work experience showed that the largest group (39%) had between 6 and 10 years of experience, while individuals with more than 10 years of experience constituted just 14% of the sample. Besides, employees having less than one year of experience represented 12%, while respondents with 1-5 years of experience represented 35% of the entire sample.

(N = 358)

	Frequency	Percentage
Gender		
Male	252	70
Female	106	30
Age		
20 years and below	46	13
21-30 years	154	43
31-40 years	117	33
41-50 years	41	11
Academic qualification		
Intermediate	17	5
Undergraduate	270	75
Graduate and above	71	20
Work experience		
Less than 1 year	43	12
1-5 years	127	35
6-10 years	141	39
More than 10 years	47	14

Table 1. Demographic characteristics

4.6. Common method bias

The research included a blend of statistical and procedural techniques to counteract any common method bias [82]. At the procedural level, the research carefully delineated the variables in the questionnaire. In addition, the simplicity of each question was kept to reduce the ambiguity of each item's construction [83]. Furthermore, the study also used a two-wave data collection technique. In wave 1, employees were asked to share their experience about employee-oriented HR practices being carried out at their organization. With a two-month interval, in wave 2, employees voiced their satisfaction over career advancement and their enthusiasm in fostering innovation. At the statistical level, Harman's single-factor test was applied which accounted for 30.37 % variance expressed by the first factor thus falling below the 50% threshold [82]. Hence, Harman's single-factor test offers further confidence that the research findings are not a result of common method variance. The study, following the application of statistical and procedural methods to minimize common method bias, determined that this bias is not a significant issue.

5. Results

5.1. Analysis Strategy

This research presents unique insights into innovative work behavior through employee-oriented HR practices in SMEs. In addition, the research explores the role of career satisfaction as mediator when examining the influence of employee-oriented HR practices on IWB. As SEM has the potential of assessing the inter-relations between many constructs simultaneously, controlling measurement error and providing strong support for measuring reliability and validity [84], the study used partial least square structural equation modeling (PLS-SEM) using SmartPLS 4 for empirically examining the relationship. The PLS-SEM, with the capacity to comprehensively analyse complex models, is a widely accepted statistical method in the field of behavioral studies and business management [85]. Besides, to test the mediation analysis, the study applied a bootstrapping strategy for testing the conditional indirect effects [86]. Consistent with previous research, a two-stage approach was adopted, wherein the measurement model was evaluated before analyzing the structural model. [87].

5.2. Measurement Model

Construct reliability, convergent and discriminant validity was used for assessing the measurement model [87]. For assessing the reliability, the study checked the composite reliability of each construct. Results showed that all the values were well above the benchmark of 0.70 [88]. The validity analysis is performed through convergent and discriminant validity. The convergent validity was assessed by evaluating the factor loadings of every item against the recommended threshold of 0.7 [87], [89]. All the items have factors loading well above the threshold thus establishing convergent validity. Moreover, the average variance extracted (AVE) of all the variables was above the critical value of 0.05 [90]. The present study's AVE values ranged from the highest of 0.969 for job enrichment to the lowest value of 0.644 for job training. The values of factor loadings, CR and AVE of all the variables are represented in Table 2.

Items		Loadings
Salary (α = 0.721, CR = 0.849, AVE = 0.652)		
Sal1	I am happy with how much I am paid and how much work I get done. .	0.838
Sal2	Given my responsibilities and experience, I believe my salary is fairly positioned relative to colleagues with comparable positions	0.798
Sal3	I am satisfied with my pay in comparison to the employee in similar positions at rival companies	0.786
Job enrichment (α =0.894, CR = 0.990, AVE = 0.969)		
JE1	I have to use a range of your abilities and skills to accomplish a number of tasks as part of my job	0.982
JE2	I can make independent choices regarding my work	0.976
JE3	I can organize my work as I see fit	0.974
Job stability (α =0.882, CR = 0.982, AVE = 0.964)		
JS1	If I perform well in my job, my company will not terminate me	0.981
JS2	The employees of other companies are more readily fired as compared to ours.	0.985
Job Training (α =0.821, CR = 0.878, AVE = 0.644)		
JT1	Our company provides us with chances to enhance and broaden their knowledge. .	0.743
JT2	Our company offers training that enhances the knowledge, skills and abilities of our employees.	0.715
JT3	Our staff members have the chance to enhance their competence by receiving training customized to meet their individual needs.	0.875
JT4	The training need assessment is regularly conducted in our organization.	0.862
Career Satisfaction (α =0.802, CR = 0.955, AVE = 0.811)		
CS1	I am happy with the professional accomplishments I have attained	0.931
CS2	I am satisfied with my progress in achieving my overall career goals.	0.852
CS3	I am happy with the progress I have made in attaining my monetary goals	0.932
CS4	I am satisfied with the career advancement goals attained in my professional life	0.931
CS5	I believe I have made acceptable progress in achieving my goals of new skills development	0.852

Innovative Work Behavior (α =0.863, CR = 0.975, AVE = 0.865)		
IWB1	The workers in our organization search for new technologies, processes, techniques, and/or product ideas	0.869
IWB2	The employees of our organization generate creative ideas	0.896
IWB3	The employees in our company promote and champions ideas to others	0.952
IWB4	The employees in our company investigate and secure funds needed to implement new ideas	0.919
IWB5	The workers in our organization device adequate plans and schedules for the innovative ideas implementation	0.963
IWB6	The employees in our company are innovative	0.977

Note(s): α = Cronbach's alpha, CR = Composite reliability, AVE = Average variance extracted

Table 2. Constructs Reliability and Validity Values

In order to assess the discriminant validity, the study used Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratios [88]. The square root of every construct's AVE value was greater than its correlation with other variables, as indicated in Table 3, to evaluate the Fornell-Larcker criterion.

	CS	IWB	JE	JS	JT	Sal
CS	0.905					
IWB	0.429	0.930				
JE	0.138	0.194	0.985			
JS	0.126	0.141	0.090	0.982		
JT	0.149	0.457	0.076	0.025	0.802	
Sal	0.153	0.261	0.174	0.054	0.216	0.807

Source(s): Author's own

Table 3. Assessment of discriminant validity using Fornell-Larcker

Besides the Fornell-Larcker criteria, we also used the HTMT ratio recommended by Henseler et al., [91] for evaluating discriminant validity. Henseler et al., [91] recommended HTMT ratio cut-off values of 0.85 and 0.90. The findings of the research indicated that all the values of the HTMT ratio were below the recommended of 0.85 (Table 4). Hence, the study validated the discriminant validity of the measurement model.

	CS	IWB	JE	JS	JT	Sal
CS						
IWB	0.449					
JE	0.143	0.198				
JS	0.133	0.145	0.092			
JT	0.166	0.510	0.091	0.034		
Sal	0.177	0.294	0.196	0.062	0.271	

Source(s): Author's own

Table 4. Assessment of discriminant validity using HTMT

5.3. Structural Model

The structural model aims to understand a relation between the variables of the study [91]. The structural model evaluation comprises five steps: significance of the structural model, assessment of collinearity, coefficient of determination (R^2), f^2 (effect size) and Q^2 value (predictive relevance) [90]. For assessing the potential multicollinearity problem, variance inflation factors (VIF) were applied. The results reported that VIF mean value (1.351) and the highest value (2.13) were lower than the benchmark value of 3 [92]. Thus, there was no multicollinearity issue in the study. To determine that the proposed relationships are not spurious, the study used the coefficient of determination (R^2) and goodness of fit test. An acceptable R^2 (0.281) was obtained for career satisfaction (0.281) and innovative work behavior (0.371) on the basis of recommended threshold value of 0.10 [93].

The f2 is assessed by examining the values: 0.35 indicates a high effect, 0.15 denotes a medium effect, and 0.02 represents a modest effect of the exogenous constructs. The values lower than 0.02 show minimal impact [89]. The analysis of the data revealed that job enrichment, salary, job training and job stability had a small effect (i.e. <0.15) on career satisfaction. This study indicates that salary, job stability, and job enrichment had a little effect (i.e., <0.15), while job training and career satisfaction significantly influenced (>0.35) employees' inclination towards innovative behavior.

The researchers are recommend to assess predictive accuracy through Geisser-Stone's Q^2 value in addition to R^2 values [94], [95]. The predictive relevance (capability test) of the model check how well it can anticipate the associations between the constructs. The positive value of endogenous variable (greater than 0) Q^2, determined through blindfolding technique, indicates predictive relevance of the theoretical model [87], [96]. The Q^2 scores for career satisfaction and innovative work behavior were positive at 0.284 and 0.311, respectively. The blindfolding procedure determines the predictive relevance or power of the theoretical model. The square root mean residual (SRMR) value of 0.069, satisfying the model's fitness, was significantly below the threshold of 0.08 [97]. Thus, the results of the study theoretically ascertain the proposed model.

5.3.1. Hypotheses Assessment

To assess the relevance of the path coefficient and analyze the relationships among employee-oriented HR practices, employee commitment, and employee innovative behavior; bootstrapping in PLS-SEM (5000 resamples) at the 0.05 significance level was employed to generate bootstrap t-statistics, standard errors, and p-values. Besides, recent studies have recommended that p-values are not an acceptable or adequate criterion for testing the significance of the proposed hypotheses, rather professing that p-values be reported along with confidence intervals and effect sizes (F^2) as shown in Table 5 [98].

5.3.2. Direct Effects Analysis

The findings of the present study indicated that salary, job enrichment, job stability and job training has a direct and significant impact on innovative work behavior; hence, supporting H1a Sal → IWB ($\beta = 0.109$; $p = 0.006$), H1b JE → IWB ($\beta = 0.093$; $p = 0.017$), H1c JS → IWB ($\beta = 0.076$; $p = 0.037$), and H1d JT → IWB ($\beta = 0.375$; $p = 0.000$). Pointedly, the influence of job training on innovative work behavior was stronger as compared to other employee-oriented HR practices. Furthermore, the study also proposed that salary, job enrichment, job stability and job training directly and significantly influence career satisfaction for hypotheses H2a, H2b, H2c and H2d. The results supported the relationships' significance thereby supporting H2a Sal → CS ($\beta = 0.105$; $p = 0.006$), H2b JE → CS ($\beta = 0.101$; $p = 0.027$), H2c JS → CS ($\beta = 0.108$; $p = 0.015$), and H2d JT → CS ($\beta = 0.115$; $p = 0.011$). In addition, the study proposed the positive effect of career satisfaction on innovative work behavior. The results stated that the career satisfaction of employees is significantly associated with their innovative behavior H3 CS → IWB ($\beta = 0.334$; $p = 0.000$) thus supporting H3.

Hypotheses	Path	β-value	T-value	P-value	BC 95% CI
H1a	Sal → IWB	0.109	2.550	0.006	0.037-0.178
H1b	JE → IWB	0.093	2.132	0.017	0.022-0.166
H1c	JS → IWB	0.076	1.787	0.037	0.006-0.146
H1d	JT → IWB	0.375	8.963	0.000	0.305-0.442
H2a	Sal → CS	0.105	2.528	0.006	0.032-0.169
H2b	JE → CS	0.101	1.926	0.027	0.015-0.188
H2c	JS → CS	0.108	2.173	0.015	0.027-0.191
H2d	JT → CS	0.115	2.285	0.011	0.031-0.197
H3	CS → IWB	0.334	8.825	0.000	0.272-0.396

Note(s): Control variables were excluded from the analysis for being substantially failing to affect the results. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5. Hypotheses testing and structural relationship results

5.3.3. Mediation Effects Analysis

In order to test the mediating effects of H4a, H4b, H4c and H4d, mediation analysis, using a bias-corrected bootstrapping at 95% confidence interval, was conducted in Smart-PLS (see figure 2) [99]. The rationale of using the Hayes and Preacher bootstrapping technique (5,000 iterations) is that it is a nonparametric test that evaluates the indirect effects by repeatedly sampling the data set (Table 6). Findings show that career satisfaction (mediator) significantly influences the relationship between salary, job enrichment, job stability, job training and innovative work behavior. Thus, the findings support H4a Sal → CS → IWB ($\beta = 0.035$; $p = 0.008$), H4b JE → CS → IWB ($\beta = 0.034$; $p = 0.028$), H4c JS → CS → IWB ($\beta = 0.036$; $p = 0.021$), and H4d JT → CS → IWB ($\beta = 0.039$; $p = 0.010$). The results further indicated that the inclusion of a mediating variable resulted in diminishing the direct effect, thus career satisfaction partially mediates the relationship in the proposed model.

Path	Total Effect		Direct Effect		Indirect Effects			
	β-coefficient	P-value	β-coefficient	P-value	β-coefficient	T-value	p-value	95%CIB
H4a Sal→ CS →IWB	0.144	0.001	0.109	0.006	0.035	2.404	0.008	0.010-0.058
H4b JE → CS →IWB	0.127	0.003	0.093	0.017	0.034	1.912	0.028	0.005-0.063
H4c JS → CS →IWB	0.112	0.008	0.076	0.037	0.036	2.037	0.021	0.007-0.065
H4d JT → CS →IWB	0.413	0.000	0.375	0.000	0.039	2.312	0.010	0.011-0.066

Note(s): The mediation was tested for significance using a bias-corrected (BC) confidence interval from 5,000 bootstrap samples. CIB means confidence interval bias

Table 6: Results of mediation analysis

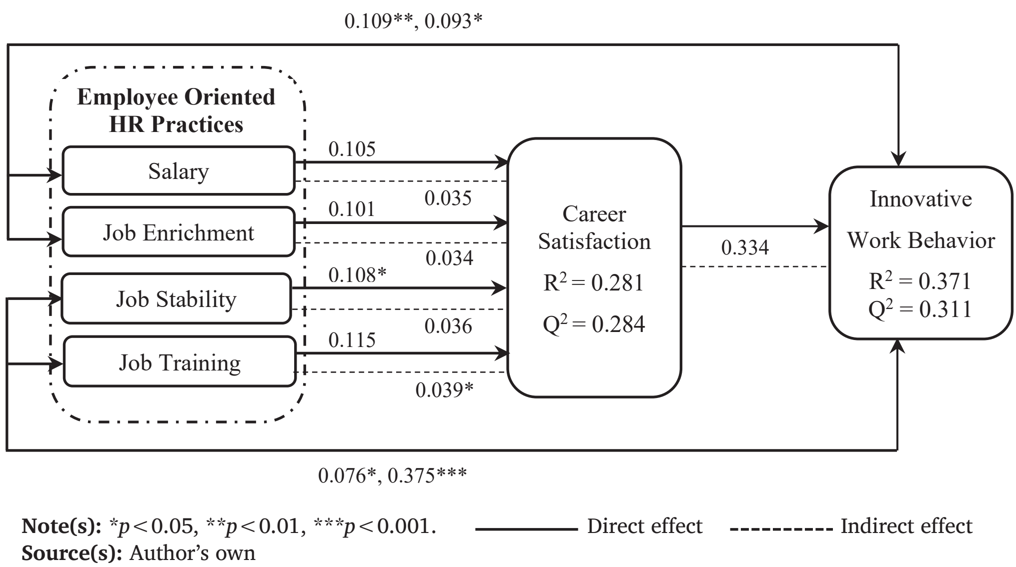

Figure 2. Regression results of mediation analysis

6. Discussion and Conclusion

This study expands the knowledge base by elucidating the influence of employee-oriented HR practices on the promotion of innovative work behavior among the workers. Furthermore, the research identifies the mediating role of career satisfaction within this relationship. To begin, the findings demonstrated that factors such as job stability, salary, job enrichment, and job training have a direct and positive impact on innovative work behavior. According to Jan et al., [27] and Mahmood et al., [35], who corroborated the findings of this study, employee-oriented HR practices influence the innovative work behavior. Secondly, the results also ascertain the positive impact of employee-oriented HR on career satisfaction. Thus, in line with the work of past researchers like Mackay [100], this research indicate that salary, job enrichment, job stability, and job training has a positive and significant role in innovative work behavior. However, the effect of job training was comparatively higher than other practices. This comparatively higher score of training might be because the majority of respondents were from a young age group (21-30) with restively less tenure in the firm, training was considered instrumental in building the skill inventory of the workforce [14].

Third, the findings indicated that career satisfaction influences the innovative behavior of employees. These finding are consistent with the work of Zhu et al., [101], who found that a higher satisfaction level of the employee increases the tendency to display innovative behavior in the workplace. Last, the study's findings indicated that career satisfaction mediates the indirect association between employee-oriented HR practices (salary, job stability, job enrichment, and job training) and innovative work behavior. These results are in line with past studies where career satisfaction was found to positively influence innovative work behavior [102]. In conclusion, utilizing social exchange theory and signaling theory, the study advocates for the implementation of employee-oriented HR practices that are essential in promoting innovative behavior. Moreover, the inclusion of career satisfaction partially mediates such relationships. Since it has the potential to encourage employees to behave in an innovative way, the study suggested that greater emphasis be placed on such HR practices. Consequently, if the company implements human resource practices that value individuals, then those employees will feel compelled to make contributions that are of great value to the corporation. Besides, signaling theory suggests that workers see employee-oriented HR practices as a signal of strategic investment in the employee of the company, consequently resulting in feelings of satisfaction from the company with the desire to reciprocate through innovative behavior.

6.1. Theoretical Implication

This study advanced theoretical knowledge in HR practices and behavioral studies in multiple ways. First, at a theoretical level, the study underpins social exchange theory and signaling theory for demonstrating the role of employee-oriented HR practices on innovative work behavior. The findings support and expand social exchange theory demonstrating the significance of employee-oriented HR practices in shaping innovative work behavior [49]. Furthermore, drawing on signaling theory, the research suggests that if organizations send out signals of ownership to the employees will be reciprocated with higher levels of discretionary behaviors like IWB [16]. Second, earlier research has highlighted the influence of HR practices on innovative work behavior, however, limited understanding has been developed regarding the identification of specific HR bundles that foster IWB [12]. In SMEs, innovative work behavior is vital for maintaining their competitive edge. Thus, the study provides empirical evidence to extend the influence of HR practices on workers' innovative behavior.

The findings indicated that employee career satisfaction significantly influences their innovative behavior. An employee is more inclined to exert additional effort and strongly align with the company's objectives and values when they feel satisfied with the organization. Consequently, they vigorously advocate, research and execute innovative ideas that are pivotal in attaining organizational objectives. Finally, the study illuminates the importance of career satisfaction in fostering innovative behavior among employees. Employee-oriented HR practices are advantageous in ascertaining the psychological satisfaction of employees in the organization. Additionally, increasing financial and non-financial investments in employees' capabilities may strengthen firms' engagement [35]. Consequently, this can give rise to innovative behavior of employees.

6.2. Practical Implications

This study delineates multiple practical implications for employees assuming managerial roles in small and medium enterprises (SMEs). First, managers should focus on implementing employee-oriented HR practices because findings advocate that such practices have a significant role in fostering innovative behavior among employees. Since training was found to have a significant impact on such behaviors, organizations should regularly carry out training programs. Second, the results of the study ascertain that career satisfaction positively influences employee innovative behavior. Thus, companies must strive to increase the satisfaction level of employees to surge the employee's sense of belongingness consequently influencing their innovative behavior. Finally, the research also revealed the mediating role of career satisfaction in elucidating the relationship between HR practices and innovative work behavior. Therefore, managers must be aware of the vitality of career satisfaction while dealing with employees' behavioral issues. Therefore, the deployment of employee-oriented HR practices can serve as a catalyst for increasing workers' satisfaction level which can be instrumental in motivating employees to implement new ideas, think creatively and behave innovatively.

7. Limitations and Future Research Directions

The study informs scholars and managers on innovative work behavior amongst employees of SEMs, while many limitations must be highlighted. This study employs a cross-sectional approach, limiting the authors' ability to make more certain conclusions. Consequently, further study may employ a longitudinal design to examine the causal relationships among the variables. This study employs a cross-sectional approach, limiting the authors' ability to make more certain conclusions. Consequently, further study may employ a longitudinal design to examine causal relationships among the variables. Secondly, the study's participants comprised employees from the SME sector in Pakistan, which constrains the generalizability of the findings. Consequently, subsequent research may investigate employees working in large organizations. Last, this study ascertains the mediating influence of career satisfaction on the relationship between employee-oriented HR practices and employee innovative behavior. Future studies, as recommended by Cooper et al., [34], can examine the alternative ways of how employee-oriented HR practices influence employee innovative behavior; such as psychological empowerment and social identity. Similarly, looking at how other positive effects of employee-oriented HR practices, such employee job crafting and proactive behavior at work, while using career satisfaction as mediator can be interesting avenue for research [27].

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Effect of Electronic Surveillance on Task Performance: Mediating Role of Digital Transformation Moderating Role of Perceived Organizational Support

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ABSTRACT

Purpose: Digital transformation is of increasing relevance for both practitioners and scholars. Modern digital technologies, services, and systems are extremely important for social development because they are currently taking place in the economy, production, and society as a whole. This study delves into the crucial domain of electronic surveillance within the healthcare sector, assessing its influence on employee task performance. It investigates the interplay between electronic surveillance, perceived organizational support, and digital transformation. Our research aims to unravel how perceived organizational support moderates the relationship between electronic surveillance and task performance while also examining the mediating role of digital transformation in this dynamic.
Design: This cross-sectional study utilizes purposive sampling to collect data from 428 participants from the healthcare sector of the province of Punjab, Pakistan.
Findings: The findings indicate that electronic surveillance positively influences task performance, with digital transformation acting as a mediator. Additionally, perceived organizational support moderates this relationship, emphasizing its vital role in optimizing task performance.
Theoretical Implications: This study advances understanding of workplace dynamics by elucidating how electronic surveillance, digital transformation, and perceived organizational support interact. It contributes valuable insights for organizational and management theories, emphasizing the need to consider these multifaceted factors in optimizing task performance.
Practical Implications: This research provides valuable insights to healthcare organizations by shedding light on these multifaceted dynamics seeking to optimize task performance amid evolving technological landscapes and increased surveillance.
Originality: This study pioneers the exploration of the intricate interplay between electronic surveillance, perceived organizational support, and digital transformation in the context of task performance in the healthcare sector of society.

Keywords: Digital transformation, Electronic surveillance, Task performance, Perceived organizational support, Society, Healthcare

1. Introduction

The concept of digital disruption, which has emerged in the twenty-first century, is transforming all established industrial environments (Kraus, 2019). As a result of the use of digital technology, new products and services are being produced, which is also changing the way work is done (through outsourcing, online platforms, robotics, improved automation, and so on (Wilburn, & Wilburn 2018).Working with digital data in real-time profoundly alters how things are managed, produced, sold, and used. Modern digital systems, services, and technology are therefore crucial for the advancement of society (Saarikko, Westergren, & Blomquist, 2020). Their incorporation into business and organization operations, engineering and technology, production enables the expansion of the range of goods and services, as well as improvements to their quality and compliance with consumer demand, productivity gains, and the formation of new value-added chains (Oztemel & Gursev 2020). Productive behaviors have been mainly associated with electronic devices such as computer, smartphones, laptops cameras and scanners make the task easy and understandable. The relationship of electronic surveillance and outcomes are interconnected.

Electronic surveillance in the workplace defines the usage of computers, smartphones. Cameras and telephones, to track the behaviors of employees for productivity effectiveness performance, and safety considerations (Yost et al., 2019). In some studies, electronic surveillance is used together with electronic monitoring and electronic devices used for betterment of the organizations and enhancing the productive behaviors of the individuals covers the concept of electronic surveillance (Holland et al., 2015).

Digital transformation (DT) encompasses digital trends at multiple levels, including technology, organizational elements, processes, particularly business model disruption, and society (Kraus, Schiavone, Pluzhnikova, & Invernizzi 2021). It has an impact on a variety of organizational characteristics, including the development of digital growth strategies, the design of internal organizational structures, and the establishment of appropriate metrics and objectives (Verhoef et al., 2019). The business sector as a whole is being revolutionized by this phenomenon, which has grown to be a very prominent research issue in a number of business research areas (such as information systems, strategy, and marketing) (Dhoni & Kumar, 2023).

Digital transformation has become an imperative across all sectors, whether it's manufacturing, finance, telecommunications, retail and consumer electronics, finance, education, transportation and logistics, energy and utilities, government and public health, retail and hospitality, or healthcare (Elayan, Aloqaily, & Guizani, 2021). Digital transformation has become a linchpin for success, reshaping the way organizations function and adapt in an ever-evolving digital landscape, so this study focuses mainly on healthcare sector transformation, which is the foremost need of any society (Mosnaim, Stempel, Van Sickle, & Stempel, 2020).

The rising relevance of DT in this industry became evident to both scholars and practitioners (Kabay, Robertson, Akella, & Lang, 2012). In today's digitally-driven workplaces, digital transformation impact plays a crucial role in many areas like electronic surveillance, task performance, data-driven decision-making, improved collaboration, skill development, etc (Dwivedi, 2020). Therefore, the focus of this study is mainly on electronic surveillance and task performance. Electronic surveillance, which involves the monitoring of employees through various digital means, can have both positive and negative effects on task performance (Dhoni & Kumar, 2023). Digital transformation acts as a bridge between these two aspects, shaping how surveillance impacts employees' ability to perform their tasks effectively by influencing how surveillance is implemented and integrated within an organization (Kraus, Schiavone, Pluzhnikova, & Invernizzi, 2021). When done strategically and with consideration for employees' privacy and well-being, it can enhance task performance by leveraging technology to improve communication, data-driven insights, efficiency, training, and employee engagement while mitigating the potential negative effects of surveillance (Wilburn & Wilburn, 2018). Perceived organizational support (POS) can have a notable impact on how employees perceive and react to electronic surveillance, which in turn can influence their task performance (Chen & Eyoun, 2021). When employees believe that their organization values and supports them, they may view electronic surveillance as a tool for their safety and security rather than as invasive monitoring. This positive perception can lead to greater acceptance of surveillance measures and a reduced sense of intrusion. In such an environment, employees may be more inclined to focus on their tasks, knowing that the organization has their best interests in mind (Huang, Achyldurdyyeva & Lin, 2021).

Following the development of the conceptual framework and a thorough literature assessment throughout this paper, the research question is, "What kind of effects of electronic surveillance are there on task performance? Does digital transformation mediate this relationship? Does perceived organizational support play any moderating role? was addressed because there is still uncertainty regarding the effects of these variables in the research, and healthcare is a sector that has recently been digitally revolutionized in Pakistan. To achieve this, firstly, a detailed background is given. Following the conceptual framework section, the study's methodology will be explained in depth. Afterward, the results obtained from this study will be put forth and discussed before the conclusion.

2. Literature Review and Hypotheses Development

2.1. Electronic Surveillance and Task Performance

In the era of rapid technological advancements, electronic surveillance has emerged as a double-edged sword in organizational contexts. While it can enhance security and monitoring, it also raises questions about its implications for employee autonomy and task performance (Lee & Gargroetzi, 2023). Electronic surveillance in the workplace has been shown to affect employee behavior, fostering a sense of being monitored, which may impact their work engagement and performance. More and more organizations tend to invest in technology to keep up with the latest product developments and reach their goals and objectives more efficiently (McParland, & Connolly, 2020). According to the American Management Association (2019), companies fired 28% of their employees in the USA owing to email misuse and 30% due to misuse of the internet in 2019, providing compelling evidence for electronic monitoring and surveillance (e-surveillance). Among the justifications for using electronic surveillance are the following: (1) to maintain employee health and workplace safety; (2) to monitor employee behavior; (3) to track performance; and (4) to ensure expected productivity (Lee & Gargroetzi, 2023).

Organizations today look for strategies to boost worker performance. Human resource managers support the growth and training of their staff members and take advantage of every chance to inspire them. This is due to the perception that good employee performance ensures organizational effectiveness (Chanana & Sangeeta 2021). Employee performance is widely acknowledged to have a two-dimensional structure. These are known as in-role and extra-role behaviors. Employees engage in in-role actions as defined by their job description. Extra-role behaviors, on the other hand, are voluntary actions that go beyond job definitions (Zhang, Luo, Zhang, & Zhao, 2019) According to these behavioral categories, performance was divided into two groups by Borman et al. (1997). Task performance is defined as the degree to which technical duties and essential job tasks are performed by an employee, whereas contextual performance refers to going above and beyond basic job requirements by being more cooperative and helpful and putting forth extra effort for the benefit of the organization. (Chandrasekara, 2019). This study focuses on task performance. Electronic surveillance procedures are typically designed to improve employee task performance at work. Monitoring an employee's behavior should assist them in completing tasks linked to their employment in order to boost productivity. Employee acceptability is therefore more likely to rise when they see electronic surveillance as a productive input (). According to earlier studies, employees are more likely to perform well on the job when they tend to accept electronic surveillance rather than oppose it (Cheng et al., 2020). So, we propose:

H1: Electronic surveillance in the workplace is positively related to the employees' task performance.

2.2. Electronic Surveillance and Digital Transformation

In the modern workplace, it is possible to track employees using computers, phones, cameras, and the Internet. The setting necessitating electronic employee surveillance is defined by human resource managers' requirement for unbiased data regarding workers' work-related behaviors and actions, including performance, productivity, and feedback. Electronic surveillance also proves to be a solution by management when remote control is required in such situations as being away from supervisors, working in virtual organizations, or when employees cannot be physically monitored. Depending on how employees view electronic surveillance, it may have varied effects on them (Aloisi & Stefano, 2022). Based on the technology-driven context in organizations, employees are more engaged with technological devices. As a natural result of using technology in the workplace more than ever, management monitors employees through electronic devices nowadays (Dhoni & Kumar, 2023).

H2: Electronic surveillance in the workplace is positively related to digital transformation.

2.3. Digital transformation Serves as a Mediating Factor that Influences the Relationship between Electronic Surveillance and Employee Task Performance

The foundation of modern society is digital transformation, which includes technologies like IoT, AI, blockchain, robotics, and 3D technologies. Digital transformation (DT) refers to “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies” (Kraus, Schiavone, Pluzhnikova, & Invernizzi, 2021). Because consumers are constantly connected to electronic devices, one of the biggest issues businesses face today is integrating and utilizing new digital technology. Numerous benefits may result from these adjustments, including increased effectiveness, access to new markets, and an improvement in brand recognition or image (Dhoni, & Kumar, 2023). According to Telukdarie et al. (2018), this revolution is fueled by both internal (such as changes in organizational structure and in the necessary skills and training) and external (such as changes in technical applications) forces. Companies need to change in two key ways in order to achieve digital transformation: first, by using technologies in the value chain, and second, by affecting their people, culture, and knowledge (Bag, Wood, Telukdarie, & Venkatesh, 2023). As a result, academic and business literature has begun to pay more attention to the mediating role of digital transformation in the relationship between electronic surveillance and task performance. Researchers have looked at how organizations are utilizing digital transformation programs to track and improve employee task performance while also taking into account possible consequences for productivity, job satisfaction, and privacy issues (Oztemel, & Gursev,2020).

Researchers like (Schertz & Berman 2019) have conducted studies that emphasize the significance of digital transformation in transforming corporate operations and processes. The implementation of technologies like data analytics, the Internet of Things (IoT), and cloud computing, which can be used to gather and analyze employee data in real-time, is a common component of these projects. Similarly, research by (Huang, 2023) looked at how electronic surveillance affected worker performance. They emphasize the potential effects of monitoring systems, like computer monitoring or GPS tracking, on task execution, including how they may improve accountability. The mediating role of digital transformation in this context is explored in work by Zheng et al. (2021). Researchers like (Nobari & Dehkordi, 2023). highlight the significance of organizational culture, industry context, and employee perceptions in shaping how digital transformation mediates the surveillance-task performance relationship. These factors can greatly influence the outcomes of digital transformation initiatives in the workplace. Therefore, the mediating role of digital transformation in the relationship between electronic surveillance and task performance is a complex and evolving area of research. It draws from various streams of literature, including digital transformation, electronic surveillance, privacy, trust, and organizational behavior, to provide insights into how organizations can navigate the challenges and opportunities presented by the digital age while ensuring optimal task performance and employee well-being. Further research is essential to exploring these dynamics in different organizational settings and industries. That's why we propose:

H3. Digital transformation serves as a mediating factor that influences the relationship between electronic surveillance and employee task performance.

2.4. Perceived Organizational Support Serves as a Moderating Factor that Influences the Relationship between Electronic Surveillance and Employee Task Performance.

Perceived organizational support refers to employees' subjective beliefs about the extent to which their organization values their contributions, cares about their well-being, and is committed to their success (Ilyas, Abid, & Ashfaq, 2022). This construct has been widely studied and recognized as a crucial factor influencing various workplace outcomes, including job satisfaction, organizational commitment, and task performance (Chen& Eyoun, 2021). Numerous studies have consistently demonstrated a positive relationship between POS and task performance. Employees who perceive higher levels of support from their organization tend to be more engaged, motivated, and committed to their tasks, and are more likely to engage in extra-role behaviors, go beyond their job descriptions, and exhibit higher levels of task performance (Huang, 2021). This positive perception of support creates a conducive work environment that fosters motivation and commitment. The impact of POS on electronic surveillance and task performance is multifaceted. On one hand, when employees perceive electronic surveillance as invasive or mistrustful, it can lead to reduced POS. A lack of privacy and autonomy may diminish job satisfaction and erode the sense of support from the organization, ultimately negatively affecting task performance. Conversely, proponents argue that limited and transparent electronic surveillance can deter unethical or unproductive behaviors, potentially enhancing task performance. Balancing the need for surveillance with employee privacy and trust is essential to maintaining a positive workplace environment (Dąbrowska, 2020).

Perceived organizational support is a critical driver of task performance, with numerous studies highlighting its positive influence. Electronic surveillance, while having potential benefits for organizations, requires careful consideration. Its impact on POS and task performance depends on various factors, including the level of transparency, trust, and ethical dimensions of its implementation. Recent research has begun to investigate the moderating role of POS in the context of electronic surveillance (Chen& Eyoun, 2021). Smith and Johnson (2020) conducted a study that suggested that employees with high levels of perceived organizational support may be less affected by electronic surveillance in terms of task performance. They argued that a supportive organizational environment may buffer the negative impact of surveillance. The

Conservation of Resources (COR) theory and Social Exchange Theory provide theoretical underpinnings for understanding these relationships. COR theory suggests that individuals strive to retain and protect their resources (e.g., autonomy), and perceived organizational support can act as a resource (Wu & Lee, 2020). Social Exchange Theory posits that employees reciprocate perceived support with increased commitment and performance (Sungu, Weng, & Kitule, 2019). Chen (2010) states that perceived organizational support has received high consideration since the 1980s. Perceived organizational support is defined as the sensitivity and opinion of an employee regarding the degree to which their involvement is appreciated and recognized by their institution, which cares about their well-being (Chen& Eyoun, 2021). According to WannYih and Hatik (2011), perceived organizational support is an employee's point of view regarding the extent to which an organization is concerned for their welfare and considers its efforts for the organization. They put in more effort when there is an indication that all efforts will be rewarded by the organization (Dąbrowska, 2020).

Positive POS combined with reasonable and transparent electronic surveillance policies can positively affect task performance. Employees who feel supported and secure are more likely to concentrate on their work, meet deadlines, and be productive (Sungu, Weng, & Kitule, 2019). Conversely, negative POS, combined with intrusive surveillance, may lead to decreased task performance due to stress and dissatisfaction (Chen& Eyoun, 2021). In summary, the impact of electronic surveillance on task performance is closely linked to how employees perceive the organization's support. Organizations should strive to maintain a positive perception of support to minimize the potential negative effects of surveillance and promote a productive work environment. Communication, transparency, and the responsible use of surveillance tools are key to achieving this balance.

H4. Perceived organizational support serves as a moderating factor that influences the relationship between electronic surveillance and employee task performance.

3. Methodology

3.1. Study Design

In this study, a cross-sectional design based on the survey method was employed, and purposive sampling techniques were utilized for participant selection. Data were collected between January 18th, 2023, and July 21st, 2023.

3.2. Sample

The sample was selected from the healthcare sector of the province of Punjab, Pakistan, which is recently digitalized and where there is intense electronic surveillance. By sampling technique, out of 214 overall health institutions in Punjab, 8 DHQ's, 12 sub-divisional hospitals, and 15 community health centers were included.

3.3. Inclusion Criteria

The survey was directed at only healthcare providers, administrative staff, IT support staff, and security personnel, as they would possess a broader vision of all the processes encompassed in the study. All participants face electronic surveillance mostly through their computers, cameras, emails, and smartphones.

3.4. Exclusion Criteria

We excluded monitoring employees who are on duty during weekends and vacations or who are visiting members of institutions or in sensitive medical procedures, protected health information handling, and had privacy concerns.

3.5. Instruments

The variables were tested using instruments that were utilized in prior investigations, ensuring the validity and reliability of the study. Multiple items were used to test each construct, and each item's score was calculated using a seven-point Likert scale ranging from "1" (strongly disagree) to "5" (strongly agree) or from "1" (never) to "7" (always). The following scales were included in the questionnaire: The eight-item Abraham et al. (2019) measure was used for electronic surveillance in the workplace. Example items are "I am working with a PC, a tablet, or a notebook. and "I am using a smartphone, a tablet, or a navigation device for orientation when on business trips. To ensure the reliability of the measurements used, the Cronbach's alpha coefficient was calculated and found to be.92 for electronic surveillance measures. To estimate task performance, a measure developed by Goodman et al. (1999) was used. "I am competent in all areas of the job, and I handle tasks with proficiency" was one of the nine items on the list. Furthermore, this scale's Cronbach's alpha value was 81. Eisenberger et al. (1986) devised eight measures for this study to assess employees' perceptions of organizational support. These items were also used in Akgunduz et al.'s (2018) research. "Our firm really cares about employees' well-being and "Our firm strongly considers employees' goals and values are two example items. We measured digital transformation using a practical adaptation of Verhoef et al.'s (2019) theoretical study. Examples of digital transformation evaluation areas include "a flexible organizational structure that allows us to face the changes resulting from DT. "Digital communication channels with employees: employee portal, email or WhatsApp groups, digital newsletter, and so on. "Digital metrics to measure customer satisfaction: web visits, digital channel visits, social network interactions, and so on."

3.6. Procedure

Various healthcare institutions were contacted, and the study was then presented to their members in order to encourage their participation. The study's design sought to assure diversity in terms of size, sector, and geographic dispersion. An institutional visit was used to gather information for conducting surveys. Cover letters were sent out to describe the research's goal, data collection techniques, and confidentiality policies. In the chosen organizations, questionnaires were distributed by hand. They were then personally gathered. To ensure that no problems arose as a result of the question's formulation, feedback was received from the institutions' communicating bodies. Out of 541 people who agreed to fill out the survey questionnaires, 428 completed them. According to the American Association for Public Opinion Research (AAPOR), the response rate is 79%, which falls into the category of Response Rate 1 (RR1). AAPOR (2015) defines response rate 1 as "the number of completed surveys divided by the number of completed surveys, plus the number of refused, non-contacts, and others, plus all cases of unknown eligibility. The study was then completed, and the researcher thanked everyone for their participation.

Employees Particular	Description	Numbers	Percentage
Gender	Female	240	45.2
	Male	188	54.8
Total		428	
Academic Qualification	Intermediate	38	8.9
	Graduation	166	38.8
	Masters	149	34.7
	MS/ MPhil or Higher	75	17.6
Total		428	
Age	21- 25 Years	122	28.5
	26-30 Years	95	22.2
	31-35 Years	72	16.9
	36-40 Years	37	8.7
	41-45 Years	50	11.6
	46-50 Years	27	6.3
	Above 50 Years	25	5.8
Total		428	100
Work Experience	Less than 1 Years	40	9.3
	1-5 Years	156	35.4
	6-10 Years	112	26.2
	11-15 Years	52	12.1
	16-20 Years	42	9.7
	Above 20 Years	26	6.03
Total		428	100

Table 1. Demographic Details

3.7. Statistical Analysis

All analyses were carried out in SPSS version 28 and SMART-PLS software version 4.0. Descriptive analysis was carried out on SPSS, all sample's characteristics e.g. gender nature, age, qualification and work experience were examined. Next, measurement of outer model was done by examining convergent & discriminant validity and loadings of all items including Cronbach 'alpha. In the second step, inner model was examined by adopting model 4 recommended by Andrew Hayes (2013). The process model allows for the assessment of the conditional effect (i.e., the influence of one variable on another that is conditioned on a third or interaction) by estimating the effect of X on Y at a specific point (or points) along the moderator and determining whether or not this effect is significant. The 95% confidence intervals (CIs) were used to determine the statistical significance of simple moderations.

4. Results

4.1. Measurement of the Model

The present study has tested the model in two phases. In the first part, the measurement of the outer model was done by examining reliability analysis on Smart-PLS version 4.0. By adopting the PLS-SEM technique. PLS-SEM (partial least squares structure equation modeling) is widely applied in many disciplines of organizational management, human resource management, social sciences, management of information systems, and operation management (Ringle et al., 2023). The PLS-SEM technique enables researchers to estimate complex constructs, models, and structural paths with no distributional assumptions in the data (Sarstedt & Cheah, 2019). Model convergent validity was assessed by examining composite reliability, average variance extracted, item outer loadings, and Cronbach alpha values. In the first step for internal consistency, Jöreskog's (1971) criteria for reliability the high level of reliability is indicated by the higher value. e.g., between 0.60 and 0.70 is acceptable and considered good," values between 0.70 and 0.90 range from "satisfactory to good, but values greater than 0.95 are problematic (Fuchs & Diamantopoulos, 2009). Cronbach's alpha is also used for internal consistency for similar thresholds. In contrast, with composite reliability, Cronbach's alpha is related to being more conservative (Henseler et al., 2015).

The first step is to see the items outer loadings. Indicator loadings should be higher than 0.70, and values greater than 0.60 are considered acceptable for the reliability of items. Before assessing the structural model and hypotheses, it is important to examine multicollinearity to ensure that there are no issues in the data set. The VIF (variance inflated factor) metric is used for assessing the issue of multicollinearity, which indicates the range of values from 0 to 3 as the significant level. Values higher than 3 indicate that there are multicollinearity issues in the data set (Hair et al., 2019). Table 2 shows that the loadings of each item are greater than 0.60, and most items have values greater than 0.70, which indicates the outer item loadings are at a significant level. Secondly, the values of the VIF of all items presented in Table 2, which rely on 1 to 3, explain that there is no issue of multicollinearity in the data.

The next step of model assessment is to address the convergent validity of each construct. Its extent converges the variances of the construct. The average variance extracted (AVE) metric is used to determine the convergent validity of each construct. For calculating the AVE, compute the mean value and square the loading of each construct and indicator. The acceptable value of AVE is 0.50 or greater, which describes at least 50 percent of the variance of its items in the construct.

Items	Factor Loadings (>0.6), Hair et al., 2019	VIF (<0.3), Hair et al., 2019	C.R (>0.7), Hair et al., 2019	AVE (>0.5), Hair et al., 2019	Cronbach's Alpha, Hair et al., 2019
Digital Transformation			0.867	0.611	0.834
DIGT1	0.848	1.446			
DIGT2	0.901	2.827			
DIGT3	0.76	1.636			
DIGT4	0.771	1.446			
DIGT5	0.667	2.09			
Electronic Surveillance			0.746	0.595	0.998
ESW1	0.734	1.323			
ESW2	0.808	1.477			
ESW3	0.733	1.293			

ESW4	0.782	1.506			
ESW5	0.777	1.906			
ESW6	0.619	1.312			
ESW7	0.619	1.419			
ESW8	0.78	1.308			
Perceived Organizational Support			0.787	0.525	0.836
POS1	0.669	1.702			
POS2	0.701	1.963			
POS3	0.818	1.808			
POS4	0.741	1.714			
POS5	0.722	1.327			
POS6	0.699	1.241			
POS7	0.822	1.289			
POS8	0.716	1.776			
Task Performance			0.895	0.506	0.879
TP1	0.714	3.229			
TP2	0.755	2.221			
TP3	0.707	1.131			
TP4	0.644	1.778			
TP5	0.769	1.229			
TP6	0.695	1.706			
TP7	0.672	1.614			
TP8	0.769	1.224			
TP9	0.74	2.224			

Table 2. Measurement of Outer Model

The next step is to examine the discriminant or divergent validity, which indicates the distinct position of each construct from the other constructs. The traditional metric proposed by Fornell and Larcker (1981) is that the AVE of each construct should be judged by the squared inter-construct correlation. The share value of all constructs should be less than the above-stated diagonal value. Table 3 indicates the values of composite reliability and Cronbach alpha are higher than 0.60 and AVE values are greater than 0.50, which indicates the significant reliability analysis and convergent validity of the constructs. Further, Table 3 also shows the distinct position of each contract by presenting the higher diagonal values of each construct from the below related items and setting the divergent reliability to a significant level.

Constructs	**Mean**	**S.D.**	**DT**	**ESW**	**POS**	**TP**
DT	7.75	1.34	0.834			
ES	5.62	1.32	0.798	0.867		
POS	4.69	1.66	0.836	0.787	0.525	
TP	6.41	1.73	0.879	0.895	0.506	0.038

DT = Digital Transformation, ES = Electronic Surveillance, POS = Perceived Organizational Support, TP = Task Performance, CA = Cronbach's alpha, CR = Composite reliability, AVE = Average Variance Extracted, DV = Discriminant Validity, Fornell and Larcker (1981)

Table 3. Discriminant Validity

4.2. Assessment of Structural Model & Hypotheses Testing

The second part of analysis regarding hypotheses testing and measurement of structural model was conducted on SMART-PLS version 4.0.2 via process macro technique. We have used Andrew Hayes process macro model no. 4 with bootstrapping 5000 resample analysis for the interaction effects proposed by Hayes (2018) of electronic surveillance on task performance by mediating the role of digital transformation. Further the moderation effects of perceived organizational support observed in this technique.

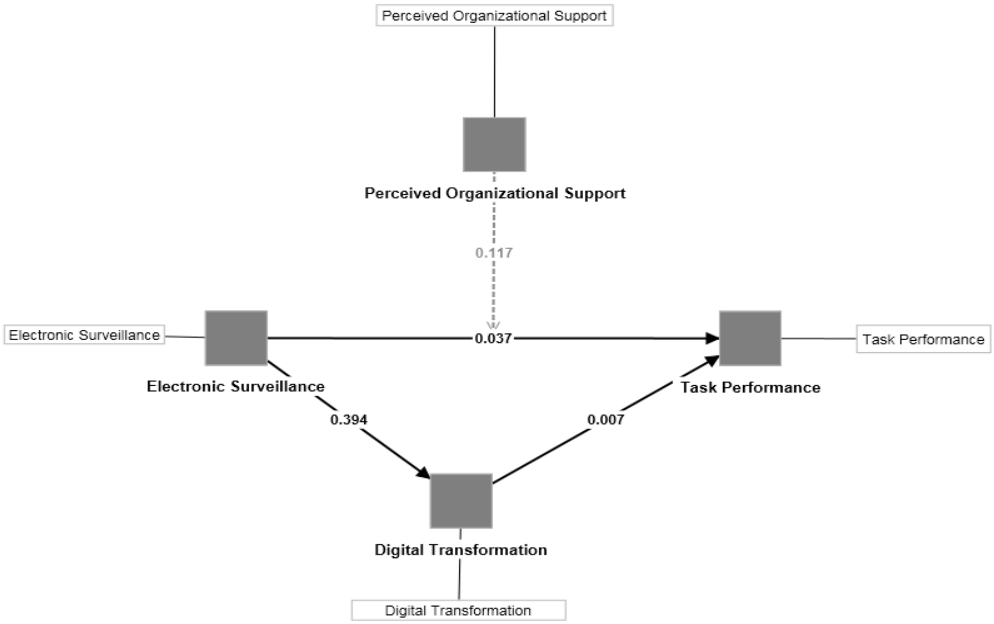

Figure 1. Path Diagram

The path diagram describes the direct positive relationship between electronic surveillance and task performance. Digital transformation positively mediates the effects of electronic surveillance on task performance, and perceived organizational support tightens the relationship between independent and dependent variables.

Hypotheses	Independent Variable	Mediator	Dependent Variable	Moderator	β	T statistics	P values	Decision
HI	ESW		TP		0.037	3.237	0.000	Accepted
H2	ESW	DIGT			0.394	3.316	0.001	Accepted
H3	ESW	DIGT	TP		0.155	9.002	0.005	Accepted
H4	ESW		TP	POS	0.117	2.649	0.008	Accepted

DT = Digital Transformation, ES = Electronic Surveillance, POS = Perceived Organizational Support, TP = Task Performance, CA = Cronbach's alpha, CR = Composite reliability, AVE = Average Variance Extracted, t = > 1.96, p = < 0.045

Table 4. Hypothesis Testing

Table 4 presents the direct and indirect effects of the study variables. The interaction of electronic surveillance with digital transformation ($\beta = 0.394$; $t = 3.316$, $p < 0.045$) The effects of electronic surveillance on task performance are positive ($\beta = 0.037$; $t = 3.237$, $p < 0.045$), which also supports the study hypotheses. The intervening role of digital transformation in task performance is positive ($\beta = 0.007$; $t = 1.964$, $p < 0.045$), which indicates the positive mediation of digital transformation between electronic surveillance and task performance. The moderation effects of perceived organizational support explain that this has strengthened the effects of electronic surveillance on task performance. i.e. ($\beta = 0.117$; $t = 2.649$, $p < 0.045$), that shows the significance level and supports the study hypotheses, which are that perceived organizational support positively moderates the effects of electronic surveillance on task performance.

4.3. Moderation Slope

The moderation slope was shown and drawn in Fig. 2, verifying the interaction term (ES x POS) effects on TP, which explains that when the perceived organizational support is higher, the effects of electronic surveillance are strengthened on task performance, and employees are ready to adopt the use of technology in the presence of organizational support.

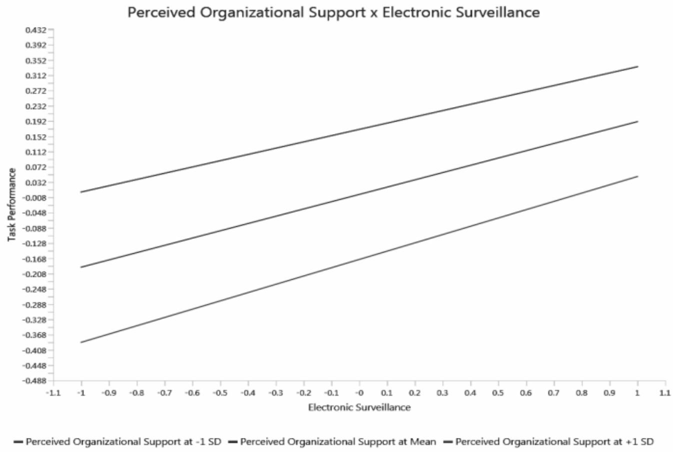

Figure 2. Moderation Slope

Perceived organizational support positively moderates the relationship between electronic surveillance and task performance.

5. Discussion

In this study, we aimed to unravel the intricate dynamics surrounding the impact of electronic surveillance on task performance while considering the moderating role of perceived organizational support and the mediating role of digital transformation. Our findings shed light on several critical points of discussion. Firstly, the results indicated that electronic surveillance has a positive impact on task performance. This suggests that, contrary to the prevailing concern that surveillance might lead to stress or decreased productivity, it can actually enhance task performance in certain contexts. Employees might perceive electronic surveillance as a means of accountability, thereby motivating them to perform better (Chen& Eyoun, 2021). The positive impact of electronic surveillance on task performance can be explained through social exchange theory (Sungu, Weng, & Kitule, 2019). According to this theory, individuals engage in reciprocal relationships with their organizations. When employees perceive that the organization is investing in monitoring their work (electronic surveillance), they may feel obligated to reciprocate with increased effort and better task performance (Dąbrowska, 2020).

Secondly, the mediating role of digital transformation was a noteworthy finding. It implies that organizations that have embraced digital transformation tend to experience a more pronounced positive effect of electronic surveillance on task performance. This emphasizes the importance of integrating advanced digital technologies to optimize task performance in surveillance-rich environments (Huang, 2021). The mediating role of digital transformation finds support in the Resource-Based View (RBV). This theory suggests that firms can gain competitive advantage by leveraging their unique resources, in this case, digital technologies (Chen& Eyoun, 2021). The integration of digital tools (mediator) enhances an organization's ability to harness the positive effects of electronic surveillance on task performance (Ilyas, Abid, & Ashfaq, 2022).

Lastly, the moderating effect of perceived organizational support underscores the significance of a supportive work environment. When employees perceive strong organizational support, the positive impact of electronic surveillance on task performance becomes even more pronounced. Organizations should prioritize fostering a culture of support to maximize the benefits of surveillance practices (Chen& Eyoun, 2021). The moderating effect of perceived organizational support aligns with social support theory. This theory posits that individuals who perceive support from their organization (in this case, support in the context of surveillance practices) tend to experience lower stress levels and better performance. Perceived organizational support acts as a buffer, making the impact of surveillance more positive (Dąbrowska, 2020).

The study's results can also be explained by the Job Demands-Resources JD-R Model. Electronic surveillance can be seen as a job demand, but when coupled with digital transformation and perceived organizational support, it can become a job resource. Job resources are known to positively impact employee engagement and performance. These theoretical underpinnings provide a framework for understanding the mechanisms through which electronic surveillance, digital transformation, and perceived organizational support collectively influence task performance. They highlight the nuanced relationships between these variables, offering valuable insights for organizations aiming to optimize their work environments in the age of electronic surveillance and digitalization.

5.1. Theoretical Implications

This paper broadens the understanding of the importance of the digital transformation process and perceived organizational support, considering the impact of both on electronic surveillance and task performance. The main contributions are the following: First, despite the importance attributed to digital transformation in organizations, there is a lack of research on its implications in the healthcare sector. The study contributes to the understanding of task performance theories by highlighting the relationship between electronic surveillance and task performance in healthcare settings. It suggests that electronic surveillance can have a significant impact on how tasks are performed by healthcare professionals, potentially improving or hindering their effectiveness. Further, the study extends digital transformation theory by emphasizing its mediating role in the relationship between electronic surveillance and task performance. It underscores that the adoption of digital technologies is not just a direct change but can also act as an intermediary mechanism affecting task performance outcomes. The study aligns with the Resource-Based View (RBV) theory by recognizing that digital transformation can be considered a valuable resource for healthcare organizations. It suggests that organizations can leverage digital transformation as a resource to enhance task performance, which is particularly relevant in resource-constrained healthcare environments (Verhoef et al., 2019). It also focuses on perceived organizational support, which aligns with social exchange theory. It suggests that healthcare professionals' perceptions of support from their organizations can moderate the relationship between electronic surveillance and task performance. This theoretical implication underscores the importance of the social dynamics within healthcare organizations. Also, it contributes to technology adoption theories by emphasizing the role of digital transformation as a mediator (Sungu, Weng, & Kitule, 2019). The adoption of electronic surveillance technology in healthcare is not just about acceptance or resistance but can be a catalyst for broader digital transformation efforts, and understanding how these changes impact task performance can inform organizational change theories and practices. The findings have implications for healthcare management theories by shedding light on the management strategies required to optimize task performance in healthcare settings. It emphasizes the importance of balancing technology implementation with organizational support.

The study brings together insights from various theoretical domains, highlighting the interdisciplinary nature of understanding the impact of electronic surveillance on task performance in healthcare. This interdisciplinary approach can enrich our understanding of complex organizational phenomena. In summary, the theoretical implications of this study advance our knowledge in multiple theoretical domains, providing a more nuanced understanding of the relationship between electronic surveillance, digital transformation, perceived organizational support, and task performance in the healthcare sector. These implications can guide future research and inform theoretical frameworks for studying technology adoption and organizational dynamics in healthcare and other sectors.

5.2. Practical Implications

Based on its theoretical contributions and the empirical analyses, this study provides a better understanding of the causal correlations among DT, ES, TP and POS. In the context of Pakistan, where healthcare systems and organizations may have unique challenges and considerations, the practical implications of the study can be the following: The study's findings on digital transformation and task performance can inform the expansion of telemedicine services in Pakistan, which is especially important for improving healthcare access in remote areas. Incorporating these considerations specific to Pakistan will help healthcare organizations in the country make informed decisions when implementing electronic surveillance systems while addressing the unique challenges and opportunities of the local healthcare landscape. Healthcare organizations should establish clear policies and guidelines for the ethical use of surveillance data to protect patient and employee privacy. This includes informed consent, data security measures, and compliance with relevant regulations such as HIPAA (Health Insurance Portability and Accountability Act). Researchers can build on this study by further investigating the specific contexts and types of electronic surveillance that are most likely to impact task performance positively or negatively in healthcare. This can lead to more tailored recommendations for different healthcare settings and roles.

The study highlights the mediating role of digital transformation. Healthcare organizations should actively invest in digital transformation initiatives that streamline processes and enhance efficiency. This may involve adopting electronic health records, telemedicine, and other digital tools that not only aid in surveillance but also improve overall task performance. Perceived organizational support plays a moderating role in the relationship between electronic surveillance and task performance, which suggests that healthcare organizations should foster a supportive work environment where employees feel valued and supported, especially when implementing surveillance systems. In summary, this research paper provides valuable insights into the complex relationship between electronic surveillance, digital transformation, perceived organizational support, and task performance in the healthcare sector. Healthcare organizations can use these practical implications to make informed decisions and optimize the implementation of electronic surveillance systems while ensuring the well-being of their employees and the quality of patient care.

5.3. Limitations and Future Research

The work has some limitations, even though it makes a substantial understanding and value contribution to the field. The study's cross-sectional design is the first drawback; a long-term study would get around it and strengthen the findings. The sample included in this study was chosen purposefully to include the most relevant participants in electronic surveillance in the health sector. Future research should incorporate a multisector sample, which makes the results more general. Furthermore, even though the questionnaires used in the study are valid and reliable, there is an important weakness about them, and it stems from their being self-evaluated. This research can provide valuable insights into how organizations can effectively leverage technology while maintaining a supportive and productive work environment for their employees.

6. Conclusion

As organizations continue to embrace electronic surveillance to ensure security and monitor employee activities, understanding its impact on employee performance is crucial. This study intends to uncover the mediating role of digital transformation in this relationship, offering insights into how organizations can harness technology to create a balance between surveillance and task performance. By doing so, organizations can enhance their operational efficiency while promoting a supportive and productive work environment.

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Associating Time Devoted to Online Gaming with Subjective Well-being, Emotional States and Affective Schedules

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ABSTRACT

Online gaming is one of the most popular students' activities associated with various aspects of their experience and behavior. This paper aims to investigate the frequency of online gaming among students and determine the association among the frequency of online gaming, emotional states, and affective schedules. The sample included 1000 undergraduate and graduate students at the University of Zagreb, studying in different science fields. The average age of the respondents was 23. The self-evaluation of time that students devote to online gaming was conducted in accordance with time categories expressed in hours devoted to online gaming. The subjective well-being was based on the self-assessment of life satisfaction questionnaire, the assessment of the frequency and intensity of unpleasant emotional state on DASS-21 questionnaire and a measure of the assessment of positive and negative affect on PANAS (Positive-PA and Negative-NA affective Schedule. The results confirm that students who are excessively involved in online gaming are less satisfied with their lives, assess unpleasant affective experience more intensively and pleasant affective experience less, compared to students who are less frequently involved in online gaming. Female students assess unpleasant emotional states of anxiety, depression, and stress more intensively than male students. Furthermore, female students assess unpleasant and pleasant affective experience more intensively than male students. These results can be applied to provide suggestions on what optimum time devoted to online gaming compared to other activities would be.

Keywords: affect, life satisfaction, online gaming

1. Introduction

Online gaming is an increasingly popular form of entertainment, and it is related to subjective well-being, emotional states, affective schedule, and problems caused by higher frequency and longer periods of online gaming.

The time devoted to online gaming corresponds to the development of excessive gaming and problematic behavior. The higher the frequency and duration of the game, the higher the level of problematic behavior which may lead to pathological gaming [1]. Kuss et al. [2] 2013 provided research results from different countries, according to which the prevalence rate of internet addiction among students ranges from 13% to 18,4%, and in general population between 6% and 15%. Problematic and pathological gaming around the world today shows an upward curve. For example, players excessively involved in online gaming spend over 40 hours per week playing online games, which equates to full-time work or more [3]. In the USA, 91% of children aged 12 to 17 practice online gaming. Furthermore, of the 318 million online gamers in the USA, at least 5 million meet the Internet Gaming Disorder criteria *(*IGD, which consequently results in personal, health, social and other issues [4], according to [5]. In 2013, Internet Gaming Disorder (IGD) was included in the 5th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5*)* by the American Psychiatric Association (APA)[6]. In 2018, World Health Organization (WHO) introduced the term 'Internet Gaming Disorder' in the International Statistical Classification of Diseases, Injuries and Causes of Death [7]. In her research, Bilić [8] states that 80.6% of children in Croatia practice online gaming. Research results, however, show that it does have both positive and negative effects.

1.1. Theoretical background

Internet Gaming Disorder (IGD) is defined by the following diagnostic criteria: preoccupation, withdrawal, tolerance, loss of control, giving up other activities, continuation, deception, escaping and negative consequences (DSM-5*)*. Mihara and Higuchi [9] 2017 conducted a research aimed at finding and systemic unification of cross-sectional studies on prevalence and longitudinal epidemiological investigations of Internet Gaming Disorder (IGD). IGD prevalence ranged from 0.7% to 27.5% in the entire sample; in the majority of studies, it was higher in men then in women and was also higher in younger population compared to the elderly. The results of cross-sectional research show that Internet Gaming Disorder (IGD) is associated with higher frequency and longer periods of online gaming [9]. In addition to gaming, IGD associated factors considered by cross-sectional studies also included family and human relations, social and school functioning, success in education and general physical and mental health. Recent studies have provided strong evidence supporting the association of internet gaming disorder (IGD) with various physical and mental health challenges. These include sleep deprivation, poor sleep quality, skipping meals, unhealthy eating habits, reduced immunity, obesity, and musculoskeletal issues such as poor posture and deformities. Additionally, excessive gaming has been linked to negative psychological and social outcomes, including dissatisfaction, functional difficulties in daily life, and disruptions in family and social relationships [10], [11], [12], [13], [14], [15].

The predictors associated with excessive gaming refer to gender, time devoted to gaming [16], [17]; and motivation. Motivation is considered an important risk factor associated with the development of problematic and pathological gaming pattern [16]. Research results show that differences in online gaming between men and women have decreased and these groups of players have become almost equal [9], whilst earlier studies showed that men were associated with higher IGD prevalence ([18], [19]; King et al., 2013 according to [9]).

Apart from the negative effects of online gaming, there are also some positive ones. Contrary to conventional beliefs that gaming leads to intellectual poverty, certain research emphasize that gaming enforces a wide range of cognitive abilities. This particularly applies to action games which encourage fast processing of information and require swift decision making, precision and concentration on the given task as well as better spatial orientation [20]). Online games are modified and updated, become more and more complex, diversified, realistic, providing appealing social, cognitive and emotional experience to players [21]. When playing, online gamers develop their logical reasoning skills [4]. Wai et al. [21] state that online games contribute to the development of spatial orientation and abilities important for achieving success in Science, Technology, Engineering and Mathematics (STEM). Bavelier et al. [22] confirm that online gamers filter irrelevant information more efficiently, develop visualization skills in 3D navigational space and develop skills of fast decision-making and attentive monitoring of sudden events in the environment. Research [4] show that, additionally to spatial skills, online games are a good means of developing problem-solving skills, practicing precision, possibilities of adjustment to new situations, developing reading and mathematical skills.

Life satisfaction means general cognitive evaluation of an individual's subjective well-being (Diener et al.,1985). Very often it is measured with one item or question: "How satisfied are you with your life overall?" all according to [23]. Numerous research included the application of positive and negative emotions/feelings through the PANAS questionnaire [24] as a means of connecting well-being/happiness and purpose/quality of life [25], [26], [27].

The time devoted to online gaming is associated with subjective well-being. Life satisfaction is a construct defining association with numerous positive life aspects such as physical and mental health, self-confidence, efficiency, and optimism. Compulsive online gaming is the result of motivation to mitigate actual dissatisfaction [28]. These studies show that what should be expected is a negative relation between the IGD and life satisfaction [19].

Von der Heiden et al. [7] compared research results of various authors and discovered that the level of addiction to online/video gaming was associated with personal characteristics, such as low self-esteem and low self-efficiency, aggression and anxiety, and that it was also connected to clinically identified symptoms of depression and anxiety disorders (Wang et al., 2018 according to [7]).

Lauri Korajlija et al. [23] conducted research on three independent samples of students and adult employees by applying the DASS-21 Scale. The goal was to determine the level of reliability, i.e., the constructive and criterial validity of measuring life satisfaction with one item. The research included application of two life satisfaction assessment tools, and additionally in every sample, application of different emotional state assessment tools (CORE-34, CORE-10 and DASS-21). This research results show that life satisfaction is negatively associated with depression, anxiety, and general emotional distress. Permanently reduced level of life satisfaction may negatively reflect on overall mental health and daily functioning [23].

Some authors point out connections of actual human contact relations and virtual world friendships. Cole and Griffiths [29] state that many gamers play with at least one person they know in real life, so online gaming only deepens their friendship and ensures it gains better quality [30]. These same authors believe that online gaming serves as a stress, anxiety, and depression release channel. Individuals prone to dysfunctional use of the internet and excessive gaming often face mental health and psycho-social behavior issues, which include poor school results, financial and marital problems, and social exclusion.

The results of the study by Isralowitz et al. [11] show that gaming disorder is associated with lower levels of psychological well-being, including increased depression, anxiety, and loneliness. It was also noted that participants with this disorder often reported lower levels of life satisfaction and social connectedness.

The construct of positive and negative affect schedule was introduced by Watson, Clark and Tellegen [24], where high positive affect schedule means good concentration, pleasure and energy and is described as a level characterized by enthusiasm and vivid behavior, whilst low positive affect schedule is characterized by sadness and apathy. High negative affect schedule includes negative emotions and stages like disgust, guilt, hatred, anxiety or fear, and low negative affect schedule comprises calmness and stability [31]. Research of positive and negative affect by applying PANAS [24] proved connection between well-being/happiness and the purpose of life [25], [26], [27]. On a sample of 480 students, association has been determined between internet addiction and symptoms of depressive conditions as well as aggressive behavior and symptoms of ADHD [32].

Negative consequences of frequent online gaming include negative effects such as stress and unsuccessful problem solving [33], lower psycho-social well-being and loneliness [19] and psychosomatic issues [34], [33]. Excessive online gaming attracts individuals who, due to their deteriorated psychological functioning, do not face problems but use online gaming to avoid actual problems and escape to a different environment. This leads to addictive behavior and clinical implications [35]. Recent research on problematic online gaming suggests that it can have significant psychological implications, particularly when individuals turn to gaming as an escape from real-world problems. Studies indicate that online gaming, while often driven by the pursuit of pleasure and positive emotions, can lead to addictive behaviors when it becomes a coping mechanism for negative emotional states like depression or dissatisfaction with life. This behavior is linked to the avoidance of responsibilities. Studies have shown that excessive gaming can lead to emotional regulation issues, where players become dependent on gaming as their primary source of emotional comfort. It has been suggested that experiencing a balance of positive and negative emotions is key to mental well-being, with a ratio favoring positive emotions, typically above 3:1. However, the intense negative emotions associated with gaming can often disrupt this balance and lead to increased frustration and anxiety [36].

Aldao et al. [37] point out that regulation strategies, such as problem recognitions and problem solving, are associated with lower level of depression symptoms. The same authors state that continuous transferring of rules and strategies in a game lead to flexible and more efficient emotional experience and that studying game advantages within a game mitigates frustration and anxiety. Whatever the case, the researchers argue that it is important to investigate to which extent online gaming is used to make the gamers feel better, and in which moment online gaming turns into a strategy to avoid actual responsibilities which leads to negative outcomes.

The global goal of this research was to determine association between the time students spend playing online games and subjective well-being, emotional states and affect schedules.

Based on this goal, the following research questions were set:

1. To determine how many hours per day, on average, students spend online gaming
2. To investigate how students assess their satisfaction with their own lives and the frequency and intensity of unpleasant emotional states (DASS-21)
3. To determine how students assess their own positive and negative affect (PANAS)
4. To identify any gender differences in self-assessment of the frequency and intensity of unpleasant emotional states of anxiety, depression and stress (DASS-21) and the intensity of positive and negative affect (PANAS)

5. To identify any connections among the variables of the frequency of online gaming, subjective well-being, the frequency and intensity of unpleasant emotional states of anxiety, depression and stress (DASS-21) and self-assessment of positive and negative affect (PANAS).

2. Research Methods

This research was conducted online with preliminary written consent of the Faculty Ethics Committee and the consent of the University of Zagreb. Research is a part of Doctoral thesis Vučić (2022)[38], supervised by coauthors. The participation was voluntary, and information was collected and processed anonymously.

2.1. Respondents' Sample

This research was conducted on a sample of up to N= 1000 students at one University in the Republic of Croatia, of whom N_F= 520 (52.0%) were female and N_M= 480 (48.0 %) were male. The average age of the respondents of both genders is expressed as arithmetic mean with standard deviation of M= 23.14, SD= 3,20. The average age of female students who participated in the research was M_F= 23.04, ds= 3,58, and of male students M_M= 23.24, ds= 2,72.

The majority of students, N= 732 (73.2%), were undergraduates, N= 199 (19.9%) of students attended the first two years of graduate studies and all *other* years of studies, including postgraduate doctoral studies, were attended by N= 69 students (6.9%).

Throughout the pilot investigation stage, details of N= 1467 students of the University in Zagreb were collected, of whom N_F= 744 (50.7%) were female students and N_M= 723 (49.3%) were male students studying at the faculties of Natural, Technical, Biomedical, Medical, Biotechnical Sciences, Social Studies, Humanities and Art Programs. The final sample was stratified in proportion to the total number of enrolled students per individual scientific / art strand, in accordance with statistic indicators of the Croatian Bureau of Statistics Announcement, ISSN 1330-0350, Zagreb, https://sredisnjikatalogrh.gov.hr and the number of students enrolled in academic year 2020-2021.

2.2. Measuring instruments

The measuring instrument listed below were used in the research, adjusted in the form of online *google form* questionnaire. For all questionnaires, the preliminary approvals for the use of measuring instruments were obtained.

1. Self-assessment of time devoted to online gaming:

The item "How often do you play online games" was used to assess the duration of online gaming. The respondents would select one of the suggested answers: a) up to 1 hour per day (up to 7 hours per week); b) between 1 and 2 hours per day (between 7 and 14 hours per week); c) between 2 to 4 hours per day (between 15 and 28 hours per week); d) between 4 to 6 hours per day (between 29 and 42 hours per week).

2. The questionnaire item on subjective well-being:

To assess their life satisfaction the respondents were asked the following question: "How satisfied are you with your life overall?" This Item was adopted from the *Subjective Well-being* Questionnaire [39]. The respondents provided their answers on a scale from 0 (entirely dissatisfied) to 10 (entirely satisfied) [39].

3. The questionnaire on assessing the frequency and intensity of unpleasant emotional states DASS-21 *(Depression, Anxiety and Stress Scale-21):*

The Questionnaire on assessing the frequency and intensity of unpleasant emotional states, Depression, Anxiety and Stress Scale DASS-21 [40] consists of three depression subscales (DASS-21D), anxiety (DASS-21A) and stress (DASS-21S). Every subscale has 7 items. The answers were provided on a Likert scale ranging from 0 ("did not apply to me at all") to 3 ("almost entirely" or "most of the time it applied to me "). The respondents would select how much a certain statement applied to them in the previous week. The score for each subscale ranged from 0 to 21. This is calculated by adding up the scores of the 7 items comprising each scale and the total theoretical range is a sum of the scores of all subscales from 0 to 63.

In Croatia a validation of Croatian adaptation of DASS-21 questionnaire was conducted in 2012 [41] indicating high reliability of the questionnaire expressed as Cronbach Alpha Coefficient (α = 0.950). In this research, the reliability of DASS-21 questionnaire expressed as Cronbach Alpha Coefficient **is** α = 0 .908 for the depression subscale, α = 0.854 for the anxiety subscale and α = 0.891 for the stress subscale [38].

4. Positive/Pleasant and Negative/Unpleasant Affect Schedule – PANAS:

The PANAS scale *(Positive-PA and Negative-NA Affective Schedule)* [24] was used to assess pleasant and unpleasant affect. PANAS, with 20 items measures the frequency of experiencing pleasant and unpleasant emotional states in the last several weeks (10 items for pleasant and 10 items unpleasant emotions). On a 5-Point Likert Scale (1 – *very little/not at all* to 5 – *extremely*) the respondents assess to what extent they are characterized by statements describing various emotional states. The reliability of the entire measuring instrument expressed as Cronbach Alpha is **α** = 0,870 [24]. The reliability (Cronbach Alpha) of PANAS' 10-item factors of *pleasant affective experience* in this research amounts to **α** = 0.880 which demonstrates very high reliability of a particular factor. The Cronbach Alpha 10-item factors of *unpleasant affective experience* in this research amounts to a high **α** = 0.919, which also means very high reliability [38].

3. Results and discussion

The presentation of results is based on answers to research questions per the following units:

3.1. Descriptive Indicators of Total Time which Students Devote to Online Gaming:

To provide answers to research issues relating to duration of online gaming, the total time students devote to online gaming was determined first: a) up to 1 hour per day (up to 7 hours per week); b) between 1 and 2 hours per day (between 7 and 14 hours per week); c) between 2 and 4 hours per day (between 15 and 28 hours per week); d) between 4 and 6 hours per day (between 28 and 42 hours per week); e) more than 6 hours per day (more than 42 hours per week). The obtained results show respondents playing online games in percentages and during periods given below: up to 1 hour per day / 7 hours per week: **60.3 %**; 1 to 2 hours per day / 7 to 14 hours per week: **17.1 %**; 2 to 4 hours per day / 15 to 28 hours per week: **14.7 %**; 4 to 6 hours per day /29 to 42 hours per week: **5.5 %**; more than 6 hours per day / more than 42 hours per week: **2.4%**.

3.2. The Results of Subjective Well-being and Assessment of the Frequency and Intensity of Unpleasant Emotional States of Depression, Anxiety and Stress

The Results of Subjective Well-being and Assessment of the Frequency and Intensity of Unpleasant Emotional States are shown below.

3.3. Descriptive Indicators of Subjective Well-being Based on Item "How satisfied are you with your life overall?"

Subjective well-being is based on the item listed in the life satisfaction questionnaire which reads: "How satisfied are you with your life overall?" [39]. This item applied on a sample of N= 1000 students provided the results given in Table 1.

How satisfied are you with your life?		N	%	M	Sd
How satisfied are you with your life overall?	1 Completely dissatisfied	17	1.7%		
	2	14	1.4%		
	3	35	3.5%		
	4	45	4.5%		
	5	67	6.7%		
	6	93	9.3%		
	7	193	19.3%		
	8	275	27.5%		
	9	170	17.0%		
	10 Completely satisfied	91	9.1%		
	Total	1000	100.0%	7.21	2.01

Table 1. The Life Satisfaction Scale Scores – Respondents' Answers to Item "How satisfied are you with your life overall?"

The subjective well-being scores presented in Table 1, slightly distributed towards the positive part of the 1-10 scale (1 being Completely dissatisfied and 10 Completely satisfied), show that the majority of respondents evaluated their life satisfaction as positive. The respondents' answers arithmetic mean is M= 7,21, SD= 2,01.

3.4. Results of the Statistical Analysis Referring to Self-assessment of the Frequency and Intensity of Emotional States DASS-21 *(*Depression, Anxiety and Stress Scale DASS-21)

To provide a detailed insight into self-evaluation of the frequency and intensity of unpleasant emotional states DASS-21 *(Depression, Anxiety and Stress Scale)* [40], the scores were analyzed according to individual subscales: Depression (DASS-21D), Anxiety (DASS-21A) and Stress (DASS-21S).

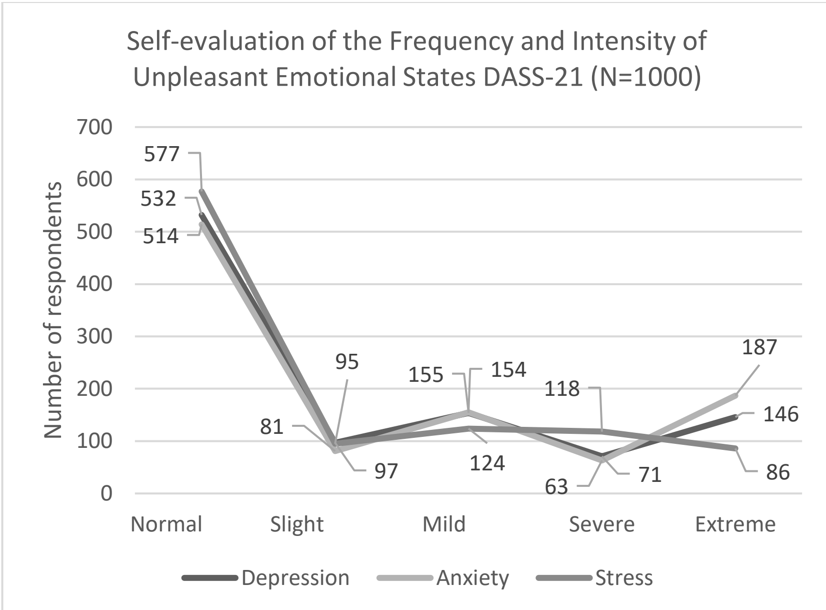

Figure 1. Distribution of results after categorization on respective subscales in DASS-21: Depression, Anxiety and Stress

The Figure 1 results show that the answers given by the majority of the respondents appear in the category of normal state of depression, anxiety, and stress, but there are also respondents in the range of slight to extreme for all three categories. The limit values on the depression, anxiety and stress self-evaluation subscales were defined according to the limit values and instructions of the authors [40]. A total of N= 187 (18.7%) of the respondents evaluated their state of anxiety as extreme or severe N= 63 (6.3%). A total of N= 146 (14.6%) evaluated their state of depression as extreme or severe N= 71 (7.1%). A total of N= 86 (8,6 %) of the respondents evaluated their state of stress as extreme or severe N= 118 (11.8%). The results indicate that these students' mental health has highly likely been impaired and would require further diagnostics and therapies. Lauri Korajlija et al. [23] also determined that life satisfaction is negatively associated with depression, anxiety and general emotional distress. The results may be interpreted in relation to the existing association between well-being/happiness and purpose/life satisfaction as determined by [25], [26], [27].

3.5. Descriptive indicators referring to self-assessment of Positive and Negative Affect, based on PANAS scale responses

Students' self-assessment of the intensity of positive and negative affect or emotional states intensity, according to the scores of the PANAS Scale applied on an N= 1000 student sample, provided results presented in Figure 2. Respondents were selected based on their answers to specific individual statements. Students evaluated their own positive and negative affective experience of active engagement, attention, excitement, power, pride, enthusiasm, thrill, determination, vigilance and interest on a 1 – 5 scale (1 – completely disagree to 5 – completely agree).

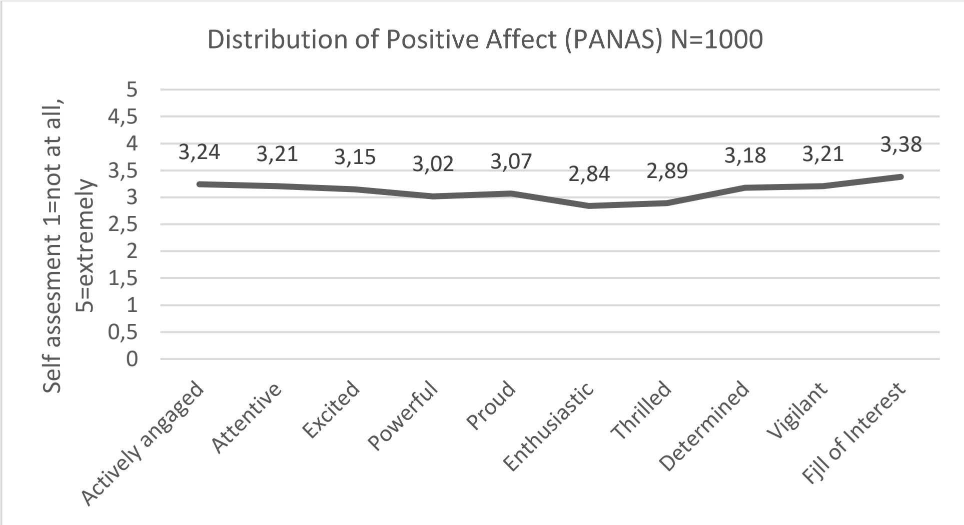

Figure 2. Intensity assessment results presented on a Positive Affect PANAS Scale

The results presented in Figure 2 diagram show a range of self-assessment arithmetic means, from M = 2.84, SD = 1.26 for enthusiasm to M = 3.38, SD = 1.12 for interest.

Additionally, on the same 1-5 scale (1 = completely disagree to 5 = completely disagree) the students assessed the intensity of their own negative affect such as wrong, nervous, hostile, quick-tempered, edgy, ashamed, scared, unhappy, timid and irritated. The results are shown in Figure 3.

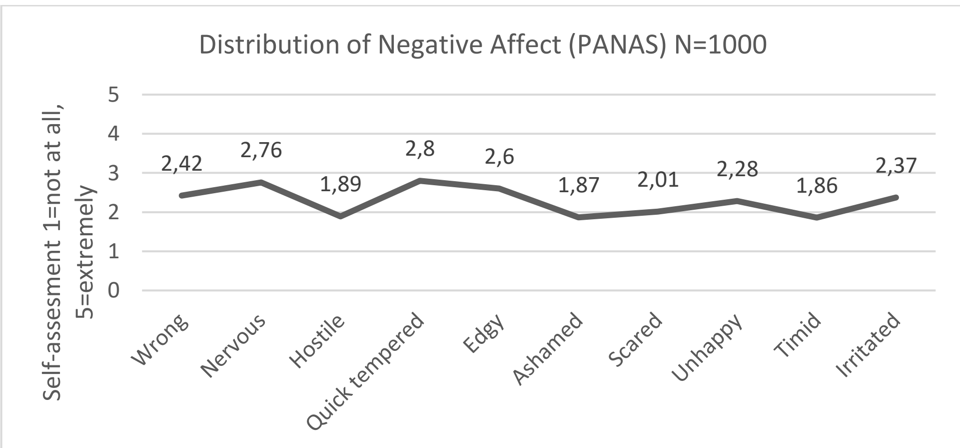

Figure 3. Intensity of Negative Affect Results Shown on Negative Affect PANAS Scale

The self-assessment results shown in Figure 3 diagram range from M = 1.86, SD = 1.17 for timidity to M = 2.8, SD = 1.32 for agitation (nervousness). These results show that the self-assessment of negative and positive states is relatively consistent and the values on the 1-5 scale are distributed around mean values. They can be compared and interpreted in relation to the results of previous research conducted by Watson et al. [24] who concluded that high intensity of positive affect was associated with high concentration, pleasure and energy, and low intensity with sadness and apathy. According to previous research [31], low intensity of negative affect is associated with calmness and stability.

3.6. Gender differences in self-assessment of Pleasant and Unpleasant Affect according to PANAS Scale and self-assessment of the Frequency and Intensity of Unpleasant Emotional States (DASS-21)

To determine any gender differences in self-assessment of pleasant and unpleasant affect and any gender differences in self-assessment of frequency and intensity of unpleasant emotional states, the results of the PANAS and DASS-21 Scale applied on the N = 1000 student sample were compared. The results are shown in Table 2.

	Gender	N	$\bar{x}$	Sd	Min	Max
DASS-21						
Depression	M	480	10.8917	11.13613		
	F	520	13.3654	11.58786		
	Total	1000	12.1780	11.43464	.00	42.00
Anxiety	M	480	7.4917	8.21984		
	F	520	12.0538	10.56100		
	Total	1000	9.8640	9.77451	.00	42.00
Stress	M	480	11.8667	9.92324		
	F	520	17.3846	11.70306		
	Total	1000	14.7360	11.22392	.00	42.00
PANAS						
Positive Affect	M	480	3.2200	.78057		
	F	520	3.0242	.82574		
	Total	1000	3.1182	.80990	1.00	5.00
Negative Affect	M	480	2.0981	.87785		
	F	520	2.4606	.99221		
	Total	1000	2.2866	.95592	1.00	5.00

Table 2. Distribution of self-assessment results referring to the frequency and intensity of unpleasant emotional states (DASS-21) and individual positive and negative affect (PANAS) according to gender (N = 1000)

The results presented in Table 2 show that male students in average achieve lower DASS-21 Scale scores (depression, anxiety, and stress) compared to their female peers, or that depression, anxiety, and stress are more common with female students. Additionally, female students demonstrate more expressed pleasant and unpleasant affective experiences per PANAS compared to male student. The arithmetic means and standard deviation are shown in Table 2.

To verify whether the differences between female and male students who participated in the questionnaires on self-assessment of the frequency and intensity of unpleasant emotional states DASS-21 and self-assessment of their own positive and negative affect based on the PANAS Scale score, are statistically significant, the t-test was applied. All T-test scores were statistically significant, and their results are shown in Table 3.

All t-test scores shown in Table 3 are statistically significant, which confirms that male and female respondents are statistically significantly different when it comes to the level of self-assessment of unpleasant emotional states per DASS-21: Female students show higher scores in self-assessment of depression, anxiety and stress that their male peers. Additionally, female students have more pronounced pleasant and unpleasant affective experiences, which was also confirmed with PANAS scale scores.

		Levene's Test for Equality of Variances		t-test for Equality of Means		
		F	Sig.	t	df	Sig. (2-tailed)
DASS-21						
Depression	Equal variances assumed	3.679	.055	-3.436	998	**.001**
	Equal variances not assumed			-3.442	996.376	.001
Anxiety	Equal variances assumed	52.903	.000	-7.579	998	.000
	Equal variances not assumed			-7.654	970.735	**.000**
Stress	Equal variances assumed	31.048	.000	-8.009	998	.000
	Equal variances not assumed			-8.061	990.959	**.000**
PANAS						
Positive Affect	Equal variances assumed	2.275	.132	3.845	998	**.000**
	Equal variances not assumed			3.854	997.432	.000
Negative Affect	Equal variances assumed	14.712	.000	-6.098	998	.000
	Equal variances not assumed			-6.128	996.226	**.000**

Table 3. T-test gender comparison of subjective well-being (DASS-21) and self-assessment of individual positive and negative affect (PANAS) on N = 1000 respondents

Considering that DASS-21 Scale is not a diagnostic instrument and is rather a means of depression, anxiety and stress symptoms level self-assessment, it can be of use to medical experts in their evaluation of risk but not for diagnostic purposes [42]. The scores obtained on the self-assessment scale ranging from slight to extreme indicate that these students need further diagnostics, support and as applicable, adequate treatment. These scores can be compared with the results of Isralowitz et al. [11], who emphasize that issues of anxiety and depression are also to be associated with internet addiction.

3.7. Correlation analysis of the time students devote to online gaming and their subjective well-being, the depression, anxiety, and stress scale (DASS-21) and the positive and negative affect schedule (PANAS)

To determine any existing correlation between the amount of time students devote to online gaming and the self-assessment of a) life satisfaction and b) positive and negative affect, the Spearman's Rank Correlation Coefficient was applied. Table 4 shows Spearman's Rank Correlation Coefficient for:

a) The analyzed online gaming frequency variables according to the following categories: up to 1 hour per day / up to 7 hours per week, 1 to 2 hours per day / 7 to 14 hours per week, 2 to 4 hours per day / 15 to 28 hours per week, 4 to 6 hours per day / 29 to 42 hours per week and more than 6 hours per day / more than 42 hours per week and subjective well-being and self-assessment of the frequency and intensity of unpleasant emotional states (DASS-21)

b) The correlation coefficients among online gaming categories according to frequency: up to 1 hour per day / up to 7 hours per week, 1 to 2 hours per day / 7 to 14 hours per week, 2 to 4 hours per day / 15 to 28 hours per week, 4 to 6 hours per day / 29 to 42 hours per week and more than 6 hours per day / more than 42 hours per week and self-assessment of positive and negative affect based on the PANAS Scale scores.

The analysis of Spearman's rank correlations presented in Table 4 indicated that the statistically significant frequency of online gaming is negatively associated with life satisfaction ($r = -0.102^{**}$, $p = 0.001$), with stress assessed by DASS–21 ($r = -0.070^{*}$, $p = -0.027$) and positive affect assessed based on answers provided in PANAS ($r = -0.079^{*}$, $p = -0.013$).

Life satisfaction demonstrated statistically significant negative correlation with the state of depression in DASS-21 ($r = -0.621^{**}$, $p = 0.000$), anxiety ($r = -0.395^{**}$, $p = 0.000$) and stress ($r = -0.458^{**}$, $p = 0.000$) and with unpleasant affect ($r = -0.501^{**}$, $p = 0.000$) and statistically positive correlation with pleasant affective experience in PANAS ($r = 0.527^{**}$, $p = 0.000$).

The DASS-21 subscale results referring to depression provide statistically significant correlation with anxiety ($r = 0.630^{**}$, $p = 0.000$), stress ($r = 0.750^{**}$, $p = 0,000$) and unpleasant affective experience in PANAS Scale ($r = 0.723^{**}$, $p = 0.000$). The result on the depression self-assessment subscale in DASS-21 is statistically significantly negatively correlated with pleasant affect according to PANAS ($r = -0.486^{**}$, $p = 0.000$). The anxiety subscale in DASS-21 negatively correlates with positive affect according to PANAS ($r = -0.269^{**}$, $p = 0.000$) and also, according to PANAS, positively correlates with negative affect ($r = 0.797^{**}$, $p = 0.000$). To conclude, lower frequency of online gaming contributes to life satisfaction, lower levels of stress and more pleasant affect. Similar results were also obtained by authors that point out to negative consequences of online gaming such as stress and unsuccessful problem solving [33], lower level of psycho-social well-being and loneliness [19] as well as psycho-somatic issues [34], [33].

			ONLINE GAMING	LIFE SATISFACTION	DASS-21			PANAS	
			1 How often do you play online games	2 How satisfied are you with your life	3 Depression	4 Anxiety	5 Stress	6 Positive affect	7 Negative affect
ONLINE GAMING	1 How often do you play online games	r	1.000	-.102**	.029	-.059	-.070*	-.079*	-.043
		p	.	.001	.368	.064	.027	.013	.171
		N	1000	1000	1000	1000	1000	1000	1000
LIFE SATISFA-CTION	2 How satisfied are you with your life	r	-.102**	1.000	**-.621****	-.395**	-.458**	**.527****	**-.501****
		p	.001	.	.000	.000	.000	.000	.000
		N	1000	1000	1000	1000	1000	1000	1000
DASS-21	3 Depression	r	.029	**-.621****	1.000	**.630****	**.750****	**-.486****	**.723****
		p	.368	.000	.	.000	.000	.000	.000
		N	1000	1000	1000	1000	1000	1000	1000
	4 Anxiety	r	-.059	-.395**	**.630****	1.000	**.750****	-.269**	**.700****
		p	.064	.000	.000	.	.000	.000	.000
		N	1000	1000	1000	1000	1000	1000	1000
	5 Stress	r	-.070*	-.458**	**.750****	**.750****	1.000	-.322**	**.797****
		p	.027	.000	.000	.000	.	.000	.000
		N	1000	1000	1000	1000	1000	1000	1000
PANAS	6 Positive affect	r	-.079*	**.527****	**-.486****	-.269**	-.322**	1.000	-.312**
		p	.013	.000	.000	.000	.000	.	.000
		N	1000	1000	1000	1000	1000	1000	1000
	7 Negative affect	r	-.043	**-.501****	**.723****	**.700****	**.797****	-.312**	1.000
		p	.171	.000	.000	.000	.000	.000	.
		N	1000	1000	1000	1000	1000	1000	1000

** Significant Correlation Level is 0.01
* Significant Correlation Level is 0.05

Table 4. Spearman's Rank Correlation Coefficient Among the Variables Relating to Online Gaming Frequency, Life Satisfaction, Self-assessment of Unpleasant Emotional States (DASS-21) and Self-assessment of Positive and Negative Affect (PANAS)

Furthermore, a negative relationship between IGD and life satisfaction was determined by Lemmens et al. [19]. The results may be interpreted in relation to the [10] research; they had determined that it was the students' population which was highly risky when it comes to internet addiction. The research conducted by [28] also indicate that online gaming is a potential way of mitigating actual dissatisfaction in real life.

4. Practical Implications

The results indicate that over one half of the students (60.3% of respondents) practice online gaming on average less than one hour per day or do not play online games at all. However, a further 17.1% or 14.7% of the respondents play online games about 2 to 4 hours or 5 to 6 hours per day, respectively. The raising concern is that 2.4% of respondents devote more than 5 hours per day to online gaming, which may negatively impact their social, emotional, and cognitive functioning.

When asked how they assess their life satisfaction, the majority of respondents replied that they were satisfied, i.e., on scale from 1 – completely dissatisfied to 10 – completely satisfied, the arithmetic mean can be estimated around 7 ($M = 7.21$, $SD = 2.01$). Nevertheless, it should be pointed out that a percentage of 11.1% ($N = 177$ respondents) express their dissatisfaction with life. These results indicate the existing need for professional assessment and, as applicable, further psychological professional treatment, which especially refers to $N = 17$ (1.7% of students who are completely dissatisfied with their own lives). Another concerning finding is that 25% of the respondents assess their state of anxiety as severe or extreme, 15.7% of students believe that their state of depression is severe or extreme and 20.4% of students experience severe or extreme stress symptoms.

Using a PANAS Scale the students assessed their own positive affect expressed in activities, attention, excitement, strength, pride, enthusiasm, thrill, determination, vigilance and interest and their own negative affect expressed as something wrong, nervous, hostile, quick-tempered edgy, ashamed, scared, unhappy, timid, and irritated. The results speak in favor of the fact that students assess affective experience around mean values of the 1-5 scale, with assessment of positive affect being slightly more intensive than the assessment of negative affect.

Male respondents on average achieve lower DASS-21 scores on subscales referring to depression, anxiety and stress compared to female respondents, i.e., depression, anxiety and stress are more expressed in female students. Furthermore, based on the scores of the PANAS Scale intended for self-assessment of the intensity of positive and negative affect, it was confirmed that in female students the statistically significant pleasant and unpleasant affective experience is more pronounced compared to their male peers.

Students who are more frequently/excessively involved in online gaming are less satisfied with their lives, often subject to stress and have less positive affective experience than students who do not play these games or play them less commonly. Students who are satisfied with their lives experience depression, anxiety and stress less commonly, their negative affect is of lower intensity and positive of higher. Self-assessment of depression is associated with anxiety, stress, and more intensive affective experience. Anxiety is negatively correlated with positive affect and positively with negative affective experience.

5. Limitations and Future Research

The main methodological limitation of this research relates to the sampling process, which was based on the proportion of enrolled students across various scientific fields. Additionally, some students did not complete the questionnaire, potentially affecting the representativeness of the sample.

In conclusion, moderate but not excessive online gaming among students appears to contribute to higher life satisfaction, reduced stress levels, and more positive and intense affective experiences. These findings could inform the development of student activity programs aimed at optimizing the time students spend on online gaming for better well-being.

The study's findings have educational implications for promoting a balanced lifestyle that supports students' mental and physical health. Future research could expand the sample to include high school students and explore the relationship between the time they spend on online gaming and their subjective well-being, emotional states, and affective experiences.

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