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CryptoProphet: Building a Cryptocurrency Portfolio App with Integrated Market Predictive Models

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Abstract

The volatility and unpredictability of cryptocurrency lead to financial losses for investors. We develop a predictive portfolio mobile app called CryptoProphet that leverages deep learning models to predict future prices and help crypto traders make informed decisions. A unique approach called the Individualized Model Selection (IMS) Strategy is adopted instead of relying on an ensemble or single model type across all cryptocurrencies. The IMS Strategy involves training each of the 30 cryptocurrencies using Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSRM (Bi-LSTM) models. Then, the best-performing model for each cryptocurrency is selected for next-day price predictions using performance metrics of Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2). This research addresses the highly volatile nature of cryptocurrencies for ensuring accurate predictions. This approach includes collecting historical data, preprocessing it, and training the models on sequences of price data. The evaluation of the models using the aforementioned metrics confirms their effectiveness. The app seamlessly integrates these predictions, providing users real-time price forecasts and essential market insights. The findings showed that the CryptoProphet portfolio app predicts prices accurately, reducing risks and maximizing profits in the volatile cryptocurrency market. Future work will focus on improving prediction accuracy by incorporating sentiment analysis and additional features such as market capitalization and volume to further improve prediction accuracy.

Keywords: Cryptocurrency, Predictive Model, Deep Learning, Portfolio Management, Real-time Data, Artificial Neural Network

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CryptoProphet: Building a Cryptocurrency Portfolio App with Integrated Market Predictive Models

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1. INTRODUCTION

Cryptocurrency is a decentralized, secured, and transparent virtual currency that has revolutionized the traditional financial system through blockchain technology (Białkowski, 2020). Nakamoto (2008) stated that Bitcoin, the first cryptocurrency, introduced the concept of digital assets that operate independently of central authorities, opening new avenues for the financial system. Thousands of cryptocurrencies have been developed since the first introduction of cryptocurrency.

According to Nakamoto (2008), the cryptocurrency ecosystem enables users to exchange digital assets directly per peer without the need for intermediaries between transactions. These platforms allow individuals to exchange cryptocurrencies securely between buyers and sellers. As explained by Nakamoto (2008) peer-to-peer exchanges empower users to participate in the cryptocurrency market on their own terms as it offers greater accessibility and flexibility compared to traditional financial system.

The cryptocurrency market has high volatility and unpredictability, which leads to financial losses for investors. The lack of reliable predictive tools increases the risk of financial losses, particularly during periods of extreme market movements. Chaudhary et al. (2020) explained that the unique characteristics of cryptocurrency, such as market liquidity, trading volume, and news, further complicate the prediction task in addition to high volatility.

Several studies have been conducted on the volatile nature of cryptocurrencies and their impact on investment. Almeida and Gonçalves (2022) reported in their research that there is a need for predictive models to manage the volatility and risks associated with cryptocurrencies. Similarly, Kim et al. (2021) suggested the importance of advanced modeling techniques for accurate predictions, and they reported that models like Bayesian Stochastic Volatility (SV) outperform traditional models in forecasting cryptocurrency.

The CryptoProphet project aims to develop a predictive portfolio application that leverages deep learning models to forecast cryptocurrency prices and help make informed decisions. In this project, a unique approach called the Individualized Model Selection (IMS) strategy was adopted instead of applying a uniform ensemble model or a single model for each cryptocurrency.

2. RELATED WORK

Cryptocurrency is a virtual currency built on blockchain technology and has transformed the financial system rapidly since the first introduction of cryptocurrency, Bitcoin, in 2009. It offers a decentralized, peer-to-peer system for transactions without intermediate traditional banking systems. This innovation has attracted significant interest from different prominent investors, speculators, and institutions, leading to the emergence of a vast ecosystem of digital assets. Sabry et al. (2020) mentioned in their report that investors face unique challenges due to high volatility, unpredictable price fluctuations, and a lack of centralized regulation besides the growth of the cryptocurrency ecosystem.

Nair et al. (2023) explored how LSTM networks can effectively model the temporal dependencies in cryptocurrency price movements. Similarly, Irfan (2022) focused on time series prediction of Bitcoin returns using machine learning models, demonstrating their ability to capture the dynamic of cryptocurrency prices. Jin and Li (2023) introduced a novel approach by combining frequency decomposition with deep learning techniques, highlighting the benefits of decomposing time series data to improve prediction accuracy.

Rather (2023) adopted a new ensemble learning method for cryptocurrency price prediction that combines multiple models to improve accuracy. Patel et al. (2020) illustrated the potential of ensemble and hybrid approaches in capturing patterns in cryptocurrency historical data, and they emphasized the robustness of stochastic neural networks for cryptocurrency price prediction in handling the stochastic nature of cryptocurrency markets.

One of the primary challenges of cryptocurrency trading is the difficulty of portfolio management across various exchange platforms. Unlike traditional financial markets, cryptocurrencies are decentralized, which results in investors holding assets in different wallets or on multiple trading platforms. Holding crypto assets on different platforms makes it challenging to track and manage portfolios effectively, resulting in inefficient management and missed opportunities. Sahu et al. (2024) stated in their report that a centralized tool to view the holding assets is crucial in making informed trading decisions because of the fast-paced nature of the cryptocurrency market.

3. APPROACH

Our work is built on a reliable solution for investors to fill the critical gap in cryptocurrency trading by providing future price predictions for making informed decisions to reduce risk and maximize profit. CryptoProphet portfolio app leverages a neural network model of deep learning to predict future prices of cryptocurrency based on the pre-trained model of 30 cryptocurrencies. The project followed valuable approaches to give the portfolio app live, from collecting historical crypto data from genuine resources, understanding and cleaning data, training models, and building the portfolio app with price prediction integration.

Design

The CryptoProphet project combines advanced deep learning techniques with a user-friendly mobile app to provide a comprehensive tool for cryptocurrency investors. It is designed to predict and provide real-time cryptocurrency prices for investors to manage portfolios, reduce loss, optimize returns, and make informed decisions. As shown in Figure 1 (Appendix), the design of the project follows structured and systematic approaches to provide price prediction and portfolio management app for investors, starting from data collection, preprocessing, model training, model selection, mobile app development using React Native, model integration with Flask Application Programming Interface (API), and real-time data extraction from CoinGecko API. The design structure ensures that each component works together smoothly to provide accurate predictions and real-time data.

Data Preprocessing

Historical price data was collected for the selected 30 cryptocurrencies using the CmcScraper library from CoinMarketCap. The collected data is preprocessed and normalized using MinMaxScaler from the scikit-learn library to ensure uniform scaling of input features, which is crucial for the performance of neural network models. The data is split into training and test sets in which the last 365 days are reserved for testing to evaluate the model’s performance on recent data. The normalized price data is then transformed into sequences of fixed length (lookback= 30 days) to capture temporal dependencies and then used to predict the next day's step. This sequence ensures that the models can learn from historical patterns to make future predictions.

Individualized Model Selection (IMS)

In the CryptoProphet project, a unique approach named the IMS strategy was proposed to select the best predictive models among many trained models for predicting the final price of each cryptocurrency. Each of the 30 cryptocurrencies was trained using three different models: LSTM, GRU, and Bi-LSTM, and then the IMS strategy was implemented instead of an ensemble model or a single model type across all cryptocurrencies. The models are evaluated to select the best-performing one for each cryptocurrency after the compilation of the training phase. Validation loss is the primary evaluation metric for selecting the final best model with the minimum validation loss.

The IMS approach's rationale is that existing ensemble techniques were inadequate due to the highly volatile nature of cryptocurrencies. Since cryptocurrencies are dynamic, their response to different predictive models can vary significantly. What works well for one cryptocurrency might not yield the same results for another. Additionally, experiments revealed that model performance could fluctuate significantly upon rerunning the training processes. For instance, while the GRU model initially performed well for cryptocurrencies like Solana and Bitcoin, its performance was inconsistent in subsequent runs. This unpredictability leads to the proposal for a more adaptable and resilient approach, leading to the development of the IMS strategy. This approach ensures that each cryptocurrency is paired with its best predictive model, thereby enhancing the overall accuracy and reliability of the predictions. This method recognizes and accommodates the unique characteristics and behaviors of different cryptocurrencies, offering a more robust solution compared to traditional ensemble methods. By leveraging the IMS strategy, CryptoProphet provides more accurate and dynamic predictions, effectively addressing the complexities of the cryptocurrency market.

Model Training
The model was trained on a MacBook Pro M1 chip, 10-core CPU, 16-core GPU, 16GB unified memory, and 1TB SSD, and it involves building and training three types of deep learning models: LSTM, GRU, and Bi-LSTM. Each model is trained on the sequences of 30 cryptocurrencies' historical preprocessed price data. The training process begins by defining the single architecture layer of each model, followed by compiling them with Adam optimizer and using MSE as the loss function. The models are then trained using training data with a 10% validation set to monitor performance. The possibility of overfitting was prevented using early stopping, which stops the training process when the validation loss no longer improves. The models are trained using the following settings: 1) Adam optimizer is used for efficient learning, 2) MSE is used as the loss function to minimize the prediction error, and 3) Early stopping is used to prevent overfitting and monitor the validation loss with patience of 10 epochs.

Mobile App Development
The mobile application development phase focuses on creating a user-friendly interface using React Native, which supports cross-platform functionality for both iOS and Android devices. The core functionality of the app is integrating real-time data retrieval, user input handling, and predictive modeling. The CryptoProphet portfolio app is composed of several key components designed to provide comprehensive functionality. As illustrated in Figure 2 in the Appendix, the AssetInput component allows users to input the cryptocurrency they have invested in, while the PurchasedPriceInput and QuantityInput components capture the purchase price and quantity of the cryptocurrency, respectively. CurrentPriceDisplay, TotalValueDisplay, ProfitLossDisplay, and ForecastDisplay are used to show the current price, total value of holdings, profit or loss, and predicted future prices of the cryptocurrencies.

Flask API
The Flask API is developed to handle requests from the mobile app and provide predictions based on user input. When a user interacts with the app and inputs their crypto name and the purchased quantity, the app sends this information to the Flask API.

The API processes the input data using the pre-trained models stored on the server. Specifically, the API normalizes the user input data, feeds it into the model to generate a prediction, and then inversely transforms the prediction back to the original price before sending it back to the mobile app. This interaction allows the app to display real-time price predictions to the user based on their input and the latest available data. The integration ensures that the models are used effectively to enhance the user experience by offering accurate and timely predictions.

Implementation
CryptoProphet implementation involves several key steps, from data collection and preprocessing to model training and user interface development. The app is built with a combination of backend and frontend using Flask API and React Native, respectively. Data preprocessing, model training, and API development were implemented with Python 3 using libraries and modules, such as Pandas, NumPy, and Matplotlib, for data processing and analysis, numerical computing, and data visualization.

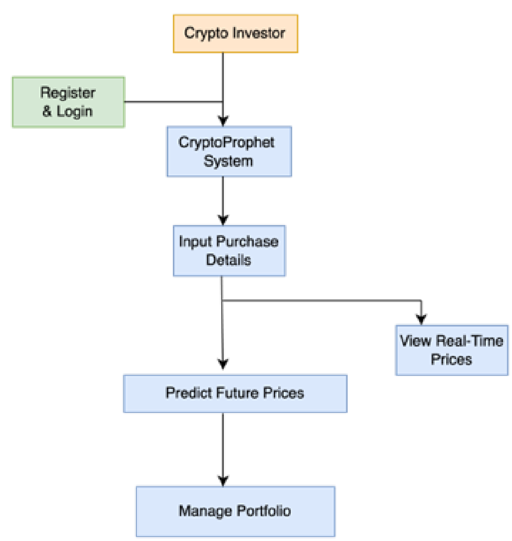

Figure 3: User Interaction Flowchart

Figure 3 shows how the users interact with the CryptoProphet portfolio app to manage their cryptocurrency investments, make informed decisions, and optimize their portfolios for maximum profitability by leveraging real-time data and predictive analytics. Users input details of their cryptocurrency investments, including the assets, purchase price, and quantity. The app then fetches real-time price data from the CoinGecko API and displays it alongside the user's input data. Additionally, the app provides future price predictions based on the trained models, giving users insights into the potential future values of their investments. This functionality enables users to make informed decisions about their cryptocurrency portfolio based on both real-time data and predictive analytics.

4. DATA COLLECTION

The list of 30 cryptocurrencies was selected aimed at representing the diverse and dynamic nature of the crypto market, data availability, and predictive relevance. This extensive list served as the foundation for subsequent evaluation and selection based on specific criteria such as market capitalization, trading volume, historical performance, and diversity in use cases and technology. Table 1 in the Appendix shows the list of selected cryptos, which includes high-market capitalization cryptos like Bitcoin (BTC) and Ethereum (ETH) due to their market dominance and rich historical data. The selection also included cryptos with significant market activities and exchanges (e.g., Binance Coin (BNB), Cardano (ADA), and Solana (SOL):), Memes (e.g., Dogecoin (DOGE), Shiba Inu (SHIB)), Metaverse and Gaming (e.g. Decentraland (MANA)), privacy coins (e.g., Monero (XMR)), Decentralized Finance (e.g., Maker (MKR), Avalanche (AVAX), ChainLink (LINK), and Fantom (FTM)), and other categories. The exclusion criteria for the selection of 30 cryptos were 1) small market and volume size, 2) recent launch without sufficient historical data, 3) lack of enough market value, and 4) low market capitalization. This careful selection of 30 cryptocurrencies allows CryptoProphet to deliver valuable predictions that can help users make informed investment decisions in the rapidly evolving cryptocurrency market.

After selecting the 30 cryptocurrencies, historical price data was meticulously collected from the beginning of each cryptocurrency's launch year up to the end of May 2024 using the CmcScraper tool from CoinMarketCap. This process ensured a comprehensive dataset that covers the entire trading history of each cryptocurrency, providing a robust foundation for analysis and prediction. As shown in Table 2 (Appendix), the collected data includes daily "Open," "High," "Low," and "Close" prices, as well as "Volume" and "Market Cap" values, ensuring a thorough understanding of each cryptocurrency's market performance over time.

Table 2 shows the data collection start date, market dominance, and the number of observations for each selected cryptocurrency. For example, BTC, with a market cap of $1.33 trillion and a dominance of 62.77%, had data collected since July 13, 2010, resulting in 5060 observations. ETH, with a market cap of $454.93 billion and a dominance of 21.44%, had data collected since August 7, 2015, totaling 3209 observations. Other notable cryptocurrencies include BNB, ADA, and SOL, each with substantial market caps and significant numbers of observations.

5. DATA ANALYSIS

In the CryptoProphet project, data analysis is crucial for transforming raw historical data into actionable insights and accurate predictions. The analysis involves the examination of the selected 30 cryptocurrencies to understand their market dynamics, identify trends, and evaluate relationships. Analytical techniques such as descriptive statistics, temporal analysis, comparative analysis, and correlation analysis are used to uncover the key patterns and behaviors in the cryptocurrency market, which is essential for making informed investment decisions and developing effective forecasting models.

Descriptive Analysis

As we learned from Table 1 in the Appendix, the predictive model in CryptoProphet can leverage the rich data to provide highly accurate predictions for major cryptocurrencies like BTC, ETH, BNB, and SOL. Their vast market cap and dominance indicate that they are less volatile compared to similar cryptocurrencies, making them reliable for long-term investment strategies. This stability can be reflected in the app's user interface by emphasizing these assets as potentially lower-risk options for users. On the other hand, cryptocurrencies with smaller market caps and lower dominance, like FTM, Quant (QNT), and NEO, often referred to as" Ethereum of China," introduce more volatility and higher risk but also potentially higher rewards. The app can incorporate these insights by offering different risk profiles for users based on these metrics. Furthermore, the number of observations for each cryptocurrency can directly impact the accuracy of the machine-learning models employed in the CryptoProphet app. Cryptocurrencies with a higher number of observations, like BTC, ETH, and LTC, allow for more robust and reliable predictive models. In contrast, new cryptos with fewer observations might need more sophisticated algorithms or hybrid models to achieve comparable predictive performance.

Lag Analysis
Comprehensive lag analysis at different time intervals was conducted to understand the influence of past prices on future prices, which is crucial for accurate price prediction. As shown in the lag plots in Figure 4 (Appendix), there is a relationship between the value of a cryptocurrency at a given time point $y(t)$ and its value at a specific lag period (1 day, 1 week, and 1 month). These plots help identify the autocorrelation in the cryptocurrency data. As we can learn from the lag plot, the 1-Day lag plot shows a strong linear relationship between a given time point $y(t)$ and the next time point $y(t+1)$. This indicates a high degree of autocorrelation at a 1-day interval, suggesting that the price of the cryptocurrency on any given day is highly predictive of its price the next day. In the CryptoProphet project, these lag plots provide critical insights for model development and feature selection. The strong autocorrelation at the 1-day lag suggests that the collected historical Close price data should be organized in a daily format. Therefore, the collected historical data from CoinMarketCap is formatted daily based on the lag analysis for the Close price. The lag plot analysis supports the design of CryptoProphet by informing the choice of input features (Close price), providing reliable short-term forecasts and well-informed long-term predictions, and making informed decisions in their cryptocurrency investments.

Correlation Matrix Analysis
Figure 5 in the Appendix shows the pairwise correlations between various cryptocurrencies for their daily Close price. A correlation value close to 1 indicates a strong positive correlation, which means the cryptocurrencies tend to move in the same direction. While a value close to -1 indicates a strong negative correlation in which the cryptocurrencies tend to move in opposite directions. Values near 0 suggest little or no linear relationship between the cryptocurrencies.

As we can learn from the correlation matrix plot, many cryptocurrencies exhibit moderate to high positive correlations with each other. For example, Cardano (ADA) with Cosmos (ATOM), Decred (DCR), and VeChain (VET) have a strong positive correlation. As a result, these assets move together in the market. Cryptocurrencies like BTC, ETH, and BNB also show high correlations with several other cryptos, reflecting their influential roles in the market. However, there are instances of weaker or even negative correlations like Render Token (RNDR) with some other assets. Understanding these correlations is crucial for the CryptoProphet project as it can significantly enhance the app's predictive modeling and portfolio management features. For example, knowing that certain cryptocurrencies are highly correlated can help improve the accuracy of selected models by leveraging the combined predictive power of these assets. This correlation insight ensures that the CryptoProphet app not only provides accurate predictions but also helps users make more informed and balanced investment decisions.

Selection of Lookback Period
In the CryptoProphet project, the lookback period is a critical parameter that defines how much historical data the model considers when making predictions. Selecting an appropriate lookback period is essential for capturing relevant patterns and trends in the cryptocurrency market, which can significantly influence the model's performance. The lookback period refers to the number of previous time steps used as input features for the predictive model. As shown in Figure 6 (Appendix), the performance metrics, including MSE, MAE, RMSE, and the R2 value, were evaluated for different lag intervals. We can learn from the plot that a lookback period of 30 days provided the lowest MSE, MAE, and RMSE while achieving the highest R2 value. This indicates that the 30-day lookback period optimally balances between capturing significant market trends and maintaining model responsiveness to recent changes. By incorporating this longer historical data span, the models can more accurately forecast future cryptocurrency prices, providing users with valuable insights for their investment decisions.

6. FINDINGS

The CryptoProphet project aims to develop a portfolio application that can predict cryptocurrency prices using advanced deep learning techniques. Rapid volatility and high stakes in the cryptocurrency market compel us to build robust and accurate forecasting models to assist traders and investors in making informed decisions. This CryptoProphet project leverages three neural network architectures, LSTM, GRU, and Bi-LSTM, to capture the complex temporal dependencies and patterns in cryptocurrency price data.

Predictive vs. Actual Plot

The CryptoProphet project has shown insightful results in predicting the prices of various cryptocurrencies. Figure 7 illustrates the predictive performance for a sample of four different cryptocurrencies: BTC, ETH, FTM, and NEO. These findings serve as examples that reveal the ability of our models to closely track the actual market prices, indicating the robustness and effectiveness of the implemented LSTN, GRU, and Bi-LSTM architectures. These four examples are representative samples out of the 30 cryptocurrencies analyzed in the CryptoProphet project. The close alignment between the actual (blue lines) and the predicted prices (red lines) indicates a high level of accuracy in the predictions.

For BTC in Figure 7, the GRU model shows a remarkable performance, with the predicted prices closely tracking the actual prices throughout the year. This is evident from the minimal divergence between the two lines, particularly during periods of both gradual and rapid price changes. This alignment suggests that the GRU model is capable of accurately capturing the complex patterns and volatility in the BTC market.

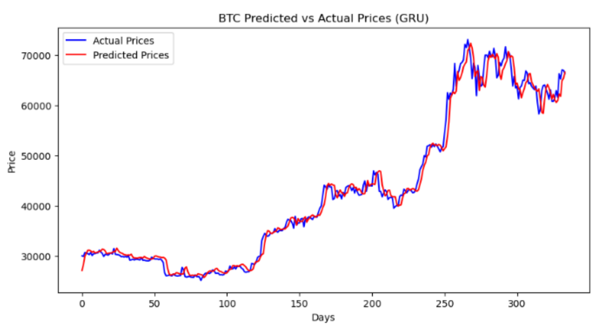

Figure 7: BTC Predictive vs. Actual Prices

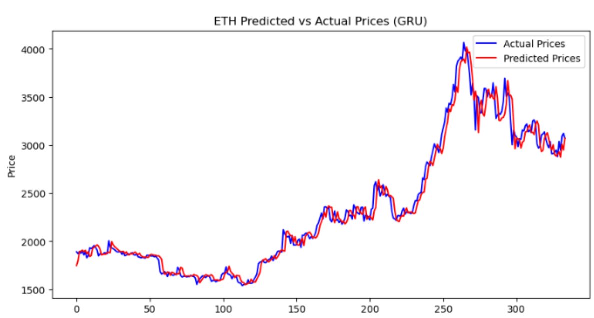

Figure 8: ETH Predictive vs. Actual Prices

For ETH, in Figure 8, the GRU model displays strong predictive accuracy similar to that of Bitcoin. The model successfully follows the sharp rise in prices around mid-year and the subsequent fluctuations. The close match between the actual and predicted prices highlights the model's ability to adapt to significant market movements and maintain its accuracy.

For FTM in Figure 9, the LSTM model shows a good fit between the actual and predicted prices. Although there are slight deviations during some of the more volatile periods, the overall trend is well captured. This indicates that the LSTM model can effectively handle the price dynamics of FTM, albeit with minor inaccuracies during high volatility.

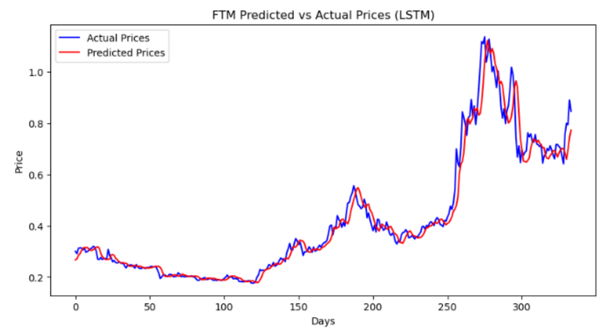

Figure 9: FTM Predictive vs. Actual Prices

For NEO in Figure 10, the Bi-LSTM model demonstrates a strong predictive capability, with the predicted prices closely mirroring the actual prices. The model performs well in tracking the general upward trend and the various peaks and troughs of the year. This close correlation suggests that the Bi-LSTM model is well-suited for forecasting NEO prices.

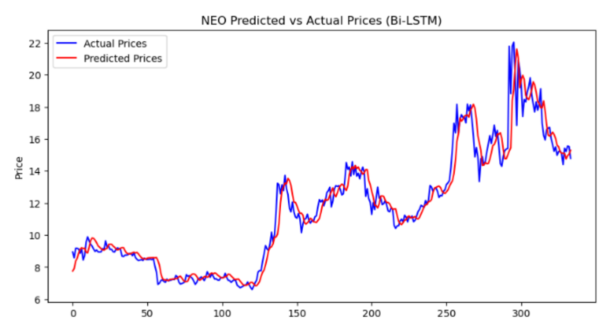

Figure 10: NEO Predictive vs. Actual Prices

The CryptoProphet project successfully integrates advanced machine learning models to provide accurate price predictions for multiple cryptocurrencies. The examples of BTC, ETH, FTM, and NEO show that the GRU, LSTM, and Bi-LSTM models can closely align with actual prices, confirming the robustness and reliability of the predictions. These consistent results across various cryptocurrencies demonstrate the app's potential as a valuable tool for investors and traders in the cryptocurrency market. The app's precise forecasts can enhance decision-making and potentially improve investment outcomes.

3D Scatter Plot
The 3D scatter plot in Figure 11 (Appendix) shows the relationship between trading volume, market capitalization, and prices for sample cryptocurrencies, BTC and ETH. Each dot represents a specific data point in time for the crypto, with the color indicating the price. The x-axis, y-axis, and z-axis represent trading volume, market capitalization, and price, respectively. As we can learn from the 3D plot, there is a clear positive correlation between the three parameters, as higher volumes and market caps are associated with higher prices. This indicates that incorporating additional features like market cap and volume can further improve prediction accuracy.

Performance Metrix
As shown in Table 3 (Appendix), the performance metrics for the CryptoProphet project confirm the effectiveness and accuracy of various deep learning models in predicting cryptocurrency prices. The metrics used to evaluate the models include MAE, MSE, RMSE, MAPE, and the R2 value.

For BTC and ETH, the GRU model achieves high accuracy with MAE values of 1146.023 and 66.780, RMSE values of 1707.753 and 98.711, and R2 values of 0.9869 and 0.9782, respectively. Similarly, for BNB and ADA, the GRU model records MAE values of 11.057 and 0.0179, RMSE values of 18.226 and 0.0275, and R2 values of 0.9829 and 0.9667. The performance is also strong for SOL, with a GRU model achieving an R2 value of 0.9812, although XRP predictions show room for improvement with an R2 of o.7785. The CryptoProphet project demonstrates the capability of advanced machine learning models, particularly GRU, LSTM, and Bi-LSTM, to provide accurate price predictions for various cryptocurrencies. The GRU model shows high accuracy across multiple cryptocurrencies, which makes it a reliable choice for forecasting. The app's robust performance metrics, such as low MAE, MSE, and RMSE values, combined with high R2 values, underscore its potential as a valuable tool for crypto investors. The consistent results across different cryptocurrencies validate the efficiency of the predictive models used in the CryptoProphet project.

7. CONCLUSIONS AND FUTURE WORK

The CryptoProphet project successfully addresses the volatility and unpredictability of the cryptocurrency market by providing accurate price prediction using deep learning models. The portfolio app integrates LSTM, GRU, and Bi-LSTM models, which conforms to excellent performance in predicting next-day prices for various cryptocurrencies. Each cryptocurrency is paired with the most suitable predictive model based on specific performance metrics by employing IMS strategies. This smart approach confirms that the unique characteristics and behaviors of different cryptos are effectively captured and improve the overall accuracy and reliability of the predictions. The portfolio app provides a user-friendly interface that presents real-time forecasts, current prices, and profit/loss calculations, which makes it an invaluable tool for investors. The findings highlight the app's capability to mitigate risks and maximize profits, thereby contributing significantly to informed decision-making in the cryptocurrency market.

The CryptoProphet portfolio app has demonstrated significant potential in assisting cryptocurrency investors with price predictions and effective portfolio management. One of the key areas for future work is to incorporate additional features such as market capitalization and trading volume. These features can offer a more detailed analysis of the market conditions and help improve the accuracy of the price predictions.

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Appendix

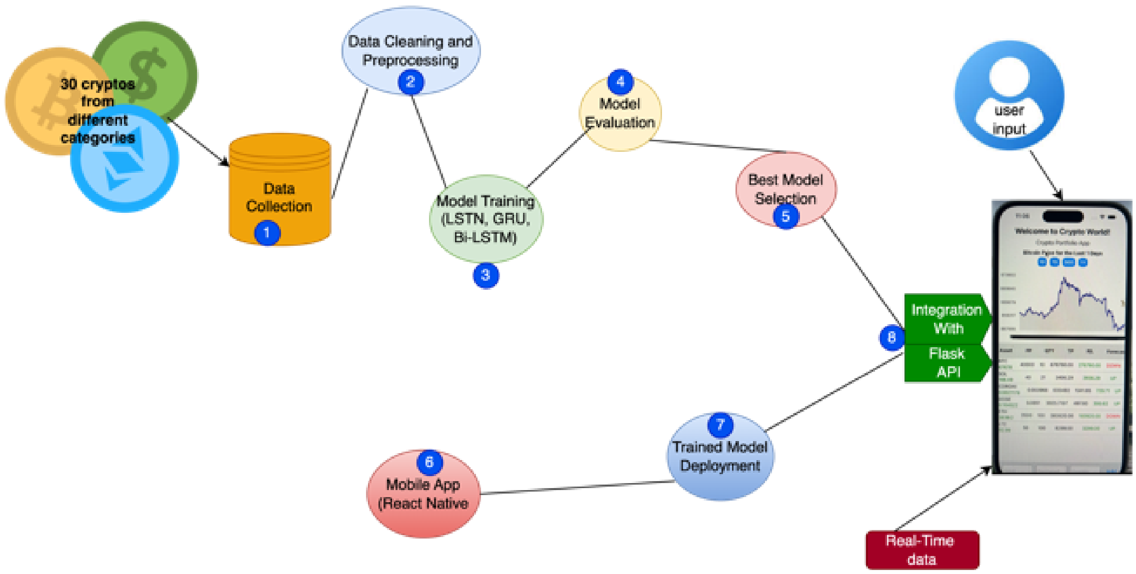

Figure 1: Design of the CryptoProphet Portfolio Mobile App

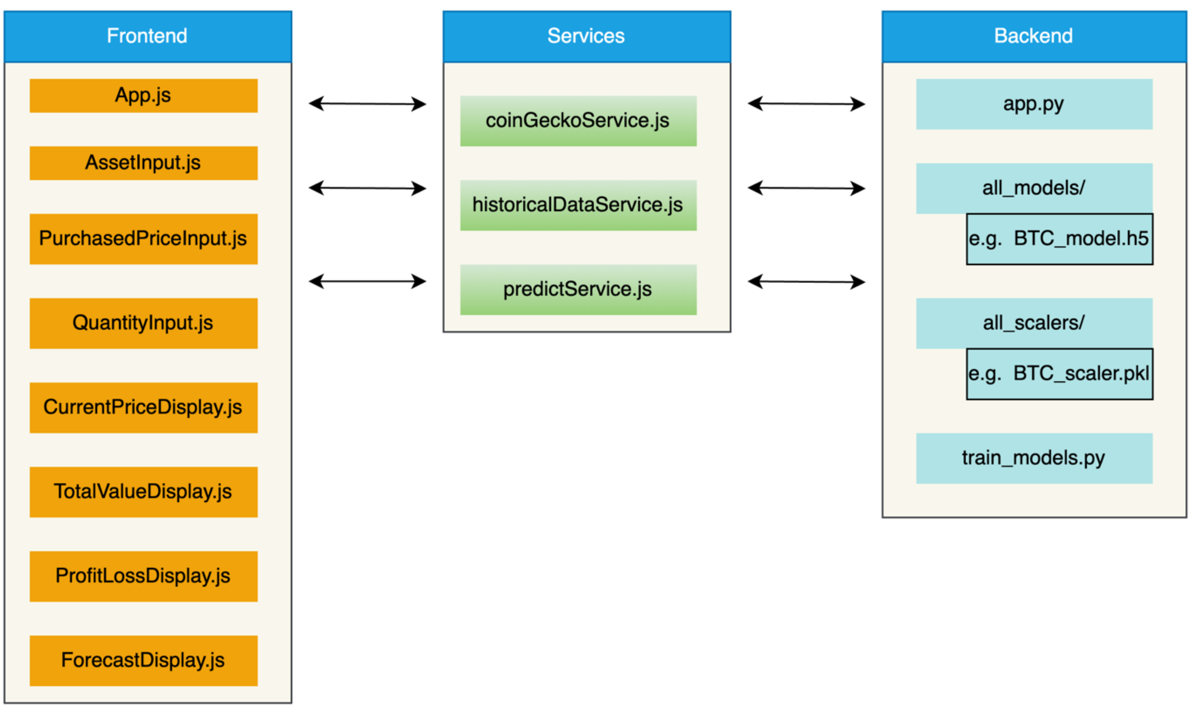

Figure 2: Interaction Flow Between Components

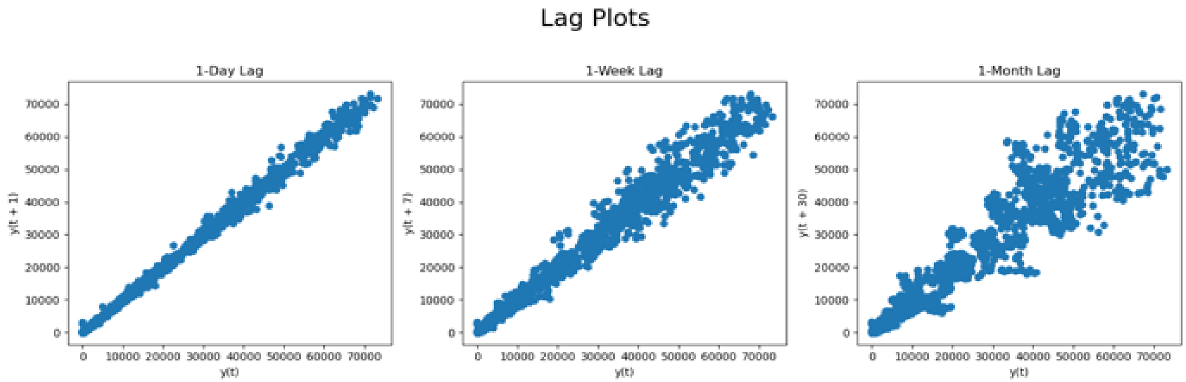

Figure 4: Lag Plots at Different Time Interval

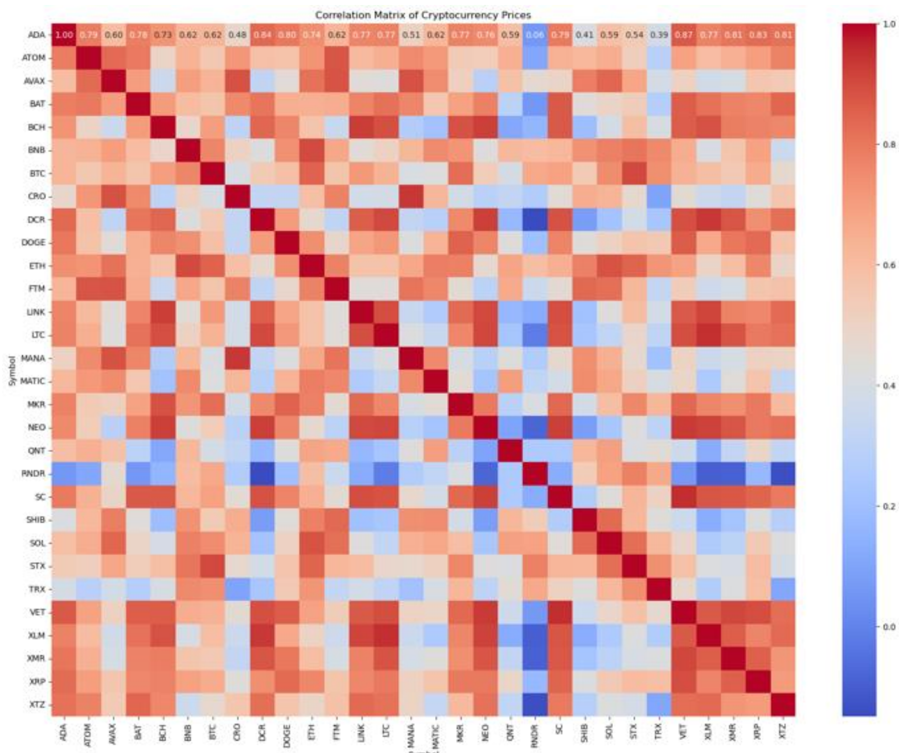

Figure 5: Correlation Matrix Plot

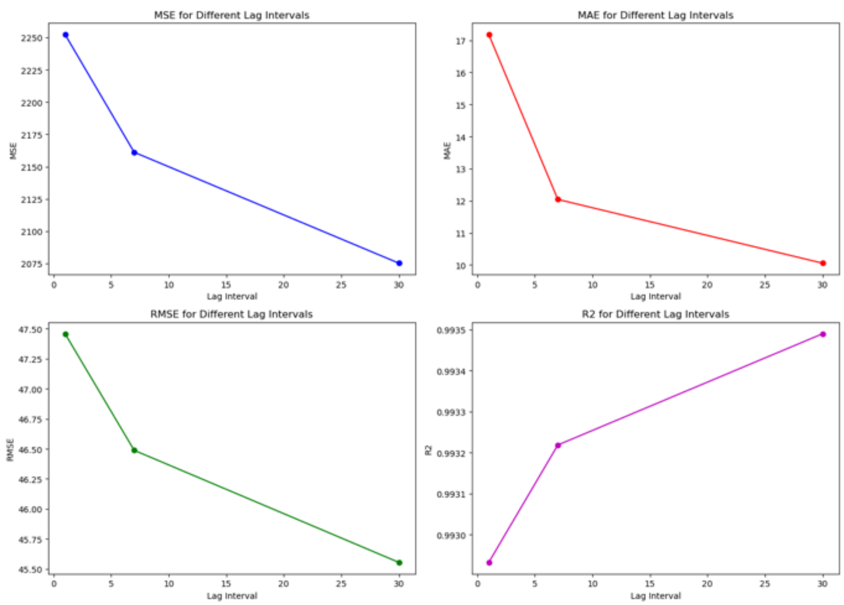

Figure 6: Lag Interval for the Lookback Period

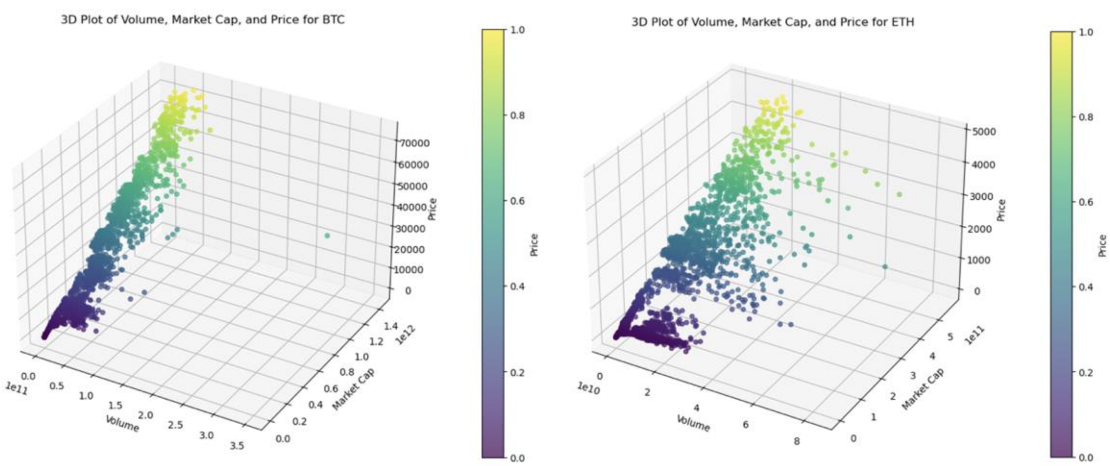

Figure 11: Additional Feature Plots

	Crypto	Symbol	Market Cap	Dominance (%)	Date Since	Number of Observations
1	Bitcoin	BTC	$1.33 Trillion	62.77%	7/13/10	5060
2	Tezos	XTZ	$944.60 Million	0.04%	7/1/18	2150
3	Decentraland	MANA	$848.82 Million	0.04%	9/17/17	2437
4	Ethereum	ETH	$454.93 Billion	21.44%	8/7/15	3209
5	Siacoin	SC	$391.06 Million	0.02%	8/26/15	3189
6	Basic Attention Token	BAT	$362.93 Million	0.02%	6/1/17	2545
7	Decred	DCR	$332.54 Million	0.02%	2/10/16	3022
8	BNB	BNB	$87.73 Billion	4.13%	7/25/17	2491
9	Solana	SOL	$76.45 Billion	3.60%	4/10/20	1501
10	XRP	XRP	$28.68 Billion	1.35%	8/4/13	3942
11	Dogecoin	DOGE	$23.06 Billion	1.09%	12/15/13	3809
12	Cardano	ADA	$16.04 Billion	0.76%	10/1/17	2423
13	Shiba Inu	SHIB	$15.07 Billion	0.71%	8/1/20	1388
14	Avalanche	AVAX	$14.25 Billion	0.67%	7/13/20	1338
15	Chainlink	LINK	$10.85 Billion	0.51%	9/20/17	2430
16	TRON	TRX	$9.80 Billion	0.46%	9/13/17	2441
17	Bitcoin Cash	BCH	$9.01 Billion	0.42%	7/23/17	2493
18	Polygon	MATIC	$6.90 Billion	0.33%	4/28/19	1849
19	Litecoin	LTC	$6.22 Billion	0.29%	4/28/13	4040
20	Render	RNDR	$3.92 Billion	0.18%	6/11/20	1439
21	Cosmos	ATOM	$3.27 Billion	0.15%	3/14/19	1894
22	Stellar	XLM	$3.08 Billion	0.15%	8/5/14	3576
23	Cronos	CRO	$3.01 Billion	0.14%	12/14/18	1984
24	Monero	XMR	$2.74 Billion	0.13%	5/21/14	3651
25	Stacks	STX	$2.68 Billion	0.13%	10/28/19	1666
26	Maker	MKR	$2.56 Billion	0.12%	1/29/17	2390
27	VeChain	VET	$2.47 Billion	0.12%	8/3/18	2117
28	Fantom	FTM	$2.23 Billion	0.11%	10/30/18	2029
29	Quant	QNT	$1.09 Billion	0.05%	8/10/18	2110
30	Neo	NEO	$1.03 Billion	0.05%	9/9/16	2810

Table 1: Number of Collected Data for each Cryptocurrency

	Date	Open	High	Low	Close	Volume	Market Cap	Symbol
0	2024-05-19	66937.930074	67694.298780	65937.177806	66278.370082	1.924909e+10	1.305732e+12	BTC
1	2024-05-18	67066.211043	67387.330366	66663.496521	66940.804410	1.671228e+10	1.318742e+12	BTC
2	2024-05-17	65231.298680	67459.459502	65119.314977	67051.874913	2.803128e+10	1.321187e+12	BTC
3	2024-05-16	66256.111817	66712.429379	64613.056046	65231.580313	3.157308e+10	1.285008e+12	BTC
4	2024-05-15	61553.989847	66454.449965	61330.408780	66267.491467	3.981517e+10	1.305167e+12	BTC
...	...	...	...	...	...	...	...	...
77418	2016-09-13	0.374469	0.375092	0.301766	0.309509	3.336910e+03	0.000000e+00	NEO
77419	2016-09-12	0.376312	0.376671	0.360443	0.374598	1.115840e+03	0.000000e+00	NEO
77420	2016-09-11	0.390948	0.398459	0.372790	0.376150	8.787000e+02	0.000000e+00	NEO
77421	2016-09-10	0.558536	0.559143	0.370960	0.391001	8.108000e+02	0.000000e+00	NEO
77422	2016-09-09	0.181483	0.558951	0.181357	0.558478	1.348860e+03	0.000000e+00	NEO

77423 rows × 8 columns

Table 2: Cryptocurrency Historical Data

crypto	model_type	MAE	MSE	RMSE	MAPE (%)	R2
BTC	GRU	1146.0229321972000	2916420.6418867500	1707.75309746074	2.526062224546220	0.9869227677820090
ETH	GRU	66.78026471892760	9743.943418532300	98.71141483401150	2.655017971449970	0.9781979175542160
BNB	GRU	11.057782877637000	332.1959967684940	18.226244724805300	2.8557689672004600	0.9828556751790460
ADA	GRU	0.017889472364757700	0.000758691206405504	0.027544349809089800	3.8602479463543400	0.9666757555366180
SOL	GRU	4.854035250080750	58.67239108778780	7.659790538114460	5.864999796478180	0.9812088934695300
XRP	GRU	0.018729255525508200	0.001134329845508730	0.033679813620457200	3.1595227463612000	0.7785169654025020
LTC	Bi-LSTM	2.923520203379290	19.37832613392660	4.402082022625950	3.6754623549424100	0.863105585084624
LINK	GRU	0.6012970016320770	0.7197413603101720	0.8483757188358070	4.7272386802480700	0.9692517604859360
DOGE	GRU	0.004610810178388240	6.83605849443954E-05	0.008268046017312400	4.024969471139600	0.9581056503990430
SHIB	GRU	7.19919392859641E-07	2.92902939802795E-12	1.7114407375156E-06	4.381922087552310	0.9542085456060000
MANA	GRU	0.023106293994709400	0.0010679181385870700	0.032679016793457400	5.0594217310575700	0.913702047802004
VET	GRU	0.0012468831566193800	3.7655912806984E-06	0.0019405131488084300	4.1377853096424000	0.967659690083565
XMR	GRU	3.6116782307255500	33.98404643104450	5.829583727080730	2.525304546294720	0.8732362591629850
BCH	GRU	18.171766180874800	1023.9637527871900	31.999433632287800	5.493657568017290	0.9271112351005340
AVAX	GRU	1.49466274076195	5.50489677241659	2.3462516430290700	5.070813859164450	0.9751543555680090
TRX	GRU	0.00454479766252581	3.05800892760126E-05	0.0055299266971644900	4.1691896982153700	0.9197688011755720
MATIC	GRU	0.03302981351632030	0.0020522104373780300	0.045301329311379200	4.2246037889708000	0.9268865155650640
CRO	GRU	0.0034410429478797300	3.31033284283272E-05	0.005753549202738010	3.516257135728380	0.9704685576649470
RNDR	GRU	0.33958221439565800	0.35661467712877600	0.5971722340571240	6.00182941944931	0.9662588770692870
XTZ	GRU	0.037505869275487300	0.0028733952662834600	0.05360406016603090	3.8557211895831400	0.9351222550756140
BAT	LSTM	0.009542970976180780	0.00018828176915124700	0.013721580417402600	4.0168782335176900	0.9123285366684590
SC	GRU	0.0004354427850027760	8.9422452394013E-07	0.0009456344557703730	5.83763196472438	0.9122506107237390
FTM	LSTM	0.02795194253367830	0.002380025628127990	0.04878550633259830	5.628912505142950	0.9591150057339260
DCR	GRU	0.9146203903271100	1.7346623507345100	1.317065811087100	5.095647665838270	0.9068616632997060
MKR	GRU	91.49046257125120	19907.86463745810	141.0952325114430	4.762330713780950	0.9662447712515940
ATOM	GRU	0.39836987342936500	0.28695069220600900	0.5356777876727850	4.322235201654790	0.9012193019140290
STX	GRU	0.09799387577272990	0.02801945174424010	0.16739011841874100	5.788644870104680	0.9702536203679250
XLM	LSTM	0.0043210773701783	4.73242277575921E-05	0.006879260698475680	3.472503977705360	0.7462423785002910
QNT	GRU	4.0850830704828800	31.903498917999600	5.64831823802445	3.7309829481302600	0.7953354456345730
NEO	Bi-LSTM	0.5653299034222750	0.8393385753969280	0.9161542312279790	4.547300440034160	0.9370619607352130

Table 3: Performance Metrics for Cryptocurrency

RAG Chatbot for Healthcare related promptsusing Amazon Bedrock

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Abstract

Applications of natural language processing (NLP) for use in large language models (LLMs) continue to evolve with technological advancements in the domain Generative AI (GenAI). The massive explosion of data, availability of scalable computing capacity and machine learning innovation, LLMs, have all led towards Generative AI (GenAI) becoming increasingly popular. A major challenge involved with base model LLMs is their tendency to hallucinate. Hallucination in LLMs refers to the output of inconsistent incoherent and sometimes incorrect information or response. This occurs as most LLMs are trained on a large amount of generic data and must be augmented using domain specific and external data for use in GenAI tasks such as chatbots, Q&A, summarization and for text generation. To address the challenge of hallucination, this study will make use of domain specific healthcare data, in the form of PDF files, alongside an FM to create a Retrieval Augmented Generation (RAG) chatbot. This study makes use of the base foundation model, Llama 2 from Amazon bedrock. Our domain specific healthcare data was sourced from relevant and reliable sources. The RAG chatbot was developed using Python and colab notebook and responses were evaluated using Rouge and Meteor, evaluation metrics for automatically generated text. The evaluation was based on three scenarios: responses less than 250 characters, more than 250 characters and combined responses from multiple LLMs. Our findings provide strong evidence that augmenting Foundation models (FMs) with domain specific data can improve the quality of the models' responses in providing reliable medical knowledge to patients.

Keywords—LLMs, Amazon Bedrock, GenAI, foundation models, llama2, hallucination.

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RAG Chatbot for Healthcare related promptsusing Amazon Bedrock

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1. INTRODUCTION

Computing technologies have provided many benefits to humans, yet they were originally built for numerical processing or structured functions. One of the challenges and natural scientific inquiry is to develop a bridge to where computers can understand human language. We refer to this today as artificial intelligence. Natural language processing (NLP) models are a part of artificial intelligence and machine learning research that started in the 1950s. Traditional ML models require labeled data that is then trained and fed into the model to be used for several NLP tasks. Many people recognize NLP through semantic analysis. NLP has limitations in its ability to process language diversity, contextual understanding, and requires extensive computing resources which limits their ability for real time processing of simultaneous transactions. Zhu, Wang, Chen, and Liu (2020)

Large language models (LLMs) were created as response to the limitations of NLP. They undergo training to learn relationships from a vast amount of data such as text documents, in a self-supervised or semi supervised process. Unlike traditional machine learning models, LLMs use multi-dimensional vectors called word embeddings to ensure that words with similar context are correctly outputted. Some common examples of LLMs include Amazon Titan, Grok, OpenAI's GPT, Cohere and Anthropic. Ovadia, Brief, Mishaeli, and Elisha (2023)

Large language models have limitations because of their training from pre-existing data. This pre-existing data can have biases to which some question the fairness and accuracy of the outputs. Another major challenge with LLMs is that they have 'hallucinations.' Hallucination in large language models is typically associated with the generation of factually inaccurate and contextually inappropriate responses. Factors such as lack of domain specific data, presence of biased training data and a lack of real-world knowledge contribute to hallucination of LLMs. The implications of hallucination in the healthcare domain can be devastating as patients require accurate and informed responses from large language models for medical and/or drug related inquiries. Jin, Yang, Chen, and Lu (2023)

Generative artificial intelligence or Gen AI as it is more commonly known is the next step of NLP and LLM that aims to mimic human conversations and generate ideas and content. Figure 1 illustrates the data flow advancement of Gen Ai over machine and deep learning. Gen AI uses an array of data inputs such as text, images, sounds and animations to produce new content and output based on the input data. Ascorbe, Campos, Domínguez, Heras, and Terroba-Reinares (2023)

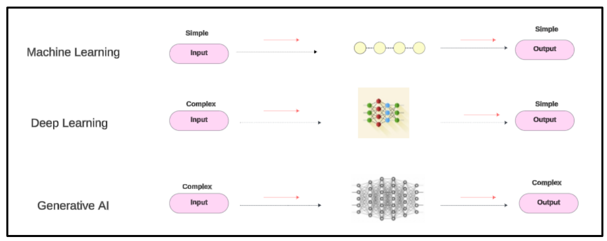

Figure 1: ML, DL, and Gen AI data flow comparison

Gen AI is the bedrock of Foundation models (FMs) mainly because FMs are trained on a large amount of unlabeled data that are used to perform several tasks. While machine learning and deep learning techniques provide simple outputs, Gen AI has the capability to accept complex data as input and output complex data. Gen AI models are enhanced by retrieval augmented generation (RAG) which can process outside information in addition to the models' original training data. Many people know RAG as a chatbot. Dou et al. (2023)

Amazon bedrock is a managed service by AWS that allows you to build and scale Gen AI applications using foundation models (FMs). It allows the extension of FMs alongside personal or proprietary data to build Retrieval Augmented Generation (RAG) applications.

This paper applies this technology to design a RAG application that caters to healthcare related queries further strengthening a domain that has limited specialized healthcare related virtual assistants or chatbots. More specifically this paper creates a RAG chatbot by augmenting a foundation model, Llama 2, with medical and healthcare related data using pdf files. The pdf files are ingested into the Llama 2 model, vector embeddings are stored in a vector store.

The development environment used for this project was Google Collab notebooks and the application was built using Python programming language. Our foundation model is accessed from Amazon bedrock using a Python library called Langchain. For the vector embedding, we used Amazon Titan Embedding which was accessed from the Amazon bedrock service while we used the FAISS (Facebook AI Similarity Search) library as our vector embeddings store.

Amazon bedrock requires authentication in order to use services. To satisfy this requirement, we used AWS Command Line Interface (CLI) to validate the credentials required by the cloud service.

Lastly, we used Streamlit for our user-facing chatbot that provided answers to healthcare related prompts. Our results show that the Augmented Llama 2 model outperforms other models which provide support to our argument that augmenting foundation models with relevant and domain specific healthcare data improves the quality of generated responses and can improve access to healthcare knowledge.

The goal of this study and our motivation is to add to the scarce research studies available in this domain and by so doing improve the research field. Ultimately, we have come up with two research questions which we will seek to answer at the end of this study.

Research Question 1- Can we reduce hallucination in LLMs by using Retrieval augmentation?

Research Question 2- To what extent does combining LLM responses improve the quality of our responses vs the base models.

2. LITERATURE REVIEW

(Biswas, Islam, Shah, Zaghouani, & Belhaouari, 2023) conducted a preliminary study to determine the potential of using ChatGPT as a medical assistant chatbot that can achieve NLP tasks relating to symptom checking, health education, diagnosis etc. One unique element of their study was that they conducted testing using the Arabic language. They fine-tuned the LLM (GPT 3.5) using open-source question and answer datasets and the evaluation of the fine-tuned model was done using human and automated metrics.

Chen et al. (2023) was interested in investigating the effects of LLM on long form automated speech recognition (ASR). They utilized YouTube videos as their long form ASR. They then studied the impacts of using an LLM to reduce the word error rate and salient term error rate on those YouTube videos. Their dataset consisted of several thousand hours of long form utterances derived from YouTube videos along with short form utterances derived from Google. The authors then used two different LLMs, the T5 and PaLm and tested it on different sizes ranging from small (60 million parameters) to XXL (118 billion parameters).

Chen et al. (2023) analyze the impact of different factors, such as the language model size, the beam size, and the utterance length, on the rescoring performance. They conclude that their method is effective and scalable for long-form speech recognition tasks and that combining LLMs improves the results in contrast to using baseline LLM singularly.

To get improved results for NLP and text classification tasks, Wei et al. (2023) compared a Distil BERT LLM base model with a fine-tuned LLM model using domain specific legal dataset. Additionally, they set out to further evaluate the performance of both LLM models by scoring an entire document on one hand and scoring sentences in a document on the other. They carried out data preprocessing on three types of datasets: confidential, non-public, and real-world legal matters. The data was cleaned up and filtered to be used for fine tuning of the distil BERT. Hugging face API was used for the finetuning of the LLM and text classification. The testing data sets of each project were then scored using the standard pretrained Distil BERT LLM and the refined Distil BERT LLM. In the first text classification job, the models are applied to entire texts by predicting using only the first 512 text tokens. The Distil BERT token limit by default is set at this value. In the second text classification job, the documents are divided into text snippets, and the models are applied to these snippets. The score for the entire document is then determined by taking the highest scoring portion from each document. The results of the study demonstrated that optimizing the LLM can enhance the effectiveness of ensuing text categorization, particularly in legal document review. The findings also demonstrate that text classification using a refined LLM performed at the snippet level can outperform document-level classification depending on the project. Whatever the document segmentation option, the optimized LLM consistently outperforms the baseline pretrained version. Finally, when compared to the refined LLM, Logistic Regression models perform well at a range of recall rates. indicating that Logistic Regression should still play a significant role in text classification.

Zhu et al. (2020) were interesting trying to provide solutions to the challenges and limitations between artificial intelligence and human language. The intent of their study was to improve the model performance of a retrieval- and generation-based dialog system by augmenting the system with a query-to-answer dataset thereby creating a many to many dialogues corpus.

Their method consisted of three steps and is shown in Figure 2. (1) extracting keywords from the dialog history (retrieval system), (2) creating expanding the keywords using word embeddings and external knowledge bases, and (3) generating new utterances based on the expanded keywords.

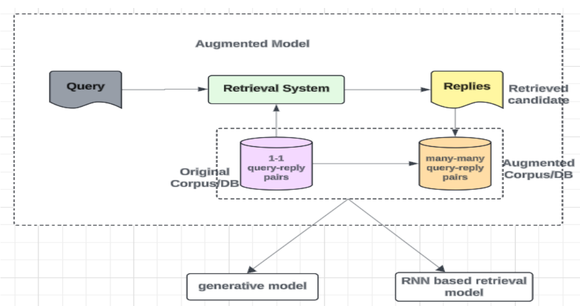

Figure 2: Dialog system for RAG application

They used two benchmark datasets and showed that it can enhance the diversity and relevance of the responses, as well as the overall quality of the dialog systems. The study results also demonstrated that as the amount of data used for training increases, the retrieval and generative models perform remarkably better when the original dataset size is set to 10K.
This helped to demonstrate how important data augmentation is. A thorough case study demonstrates their framework's capacity to produce more varied and significant expressions. The results also indicated a limit to how much data may be added to the training dataset because of the opposite performance in both the retrieval and generative dialog systems as the amount of the original data increases.

Jin et al. (2023) aimed to augment LLMs with domain specific tools leading to the reduction of hallucinations and the retrieval of specialized knowledge. The authors presented a novel method called GeneGPT which uses web APIs to answer questions relating to genomics. They used in-context learning and an enhanced decoding algorithm that recognizes and executes API requests to prompt Codex to answer the GeneTuring tasks using NCBI Web APIs. With an average score of 0.83, the results demonstrated that GeneGPT achieves state-of-the-art performance on eight tasks in the GeneTuring benchmark, significantly outperforming retrieval-augmented LLMs like the new Bing (0.44), biomedical LLMs like BioMedLM (0.08) and BioGPT (0.04), GPT-3 (0.16), and ChatGPT (0.12).

Dou et al. (2023) proposed a novel Large Language Model (ShennongGPT) specifically designed for the Chinese language to provide medication guidance and predict adverse drug reactions. ShennongGPT employs a two-stage training strategy and is illustrated in Figure 3.

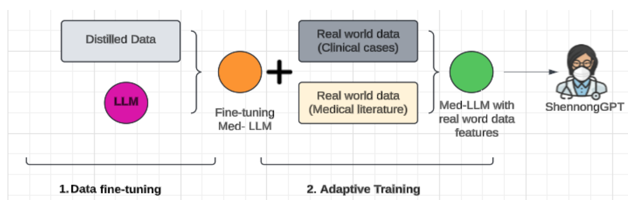

Figure 3: ShennonGPT architecture

Initially, the model learns from distilled drug databases to gain foundational knowledge on drug interactions. Subsequently, it simulates human-like decision-making processes using real-world patient data, which enhances the model's relevance and applicability in providing guidance. This approach allows ShennongGPT to excel in predicting potential adverse drug reactions and offering personalized medication advice, aiming to improve medication safety and healthcare quality. Rigorous evaluations by healthcare professionals and AI experts have underscored the superiority of ShennongGPT over existing general and specialty LLMs. However, the authors emphasize that while ShennongGPT is dedicated to research and holds promise for healthcare applications, it is not intended to replace professional medical advice. The accuracy of responses generated by LLMs cannot be guaranteed, and in cases of discomfort or distress, seeking the guidance of a qualified medical professional is strongly recommended.

Ascorbe et al. (2023) offered a novel Retrieval Augmented Generation (RAG) system designed to improve the accessibility and quality of information available for suicide prevention. Their system endeavored to address the challenge of providing accurate and reliable information to individuals seeking help in this critical area. The RAG system leverages advanced computational techniques to enhance the process of information retrieval and generation, ensuring that users receive the most relevant and supportive content.

The authors detailed the architecture of the system, which integrates a sophisticated search mechanism with a generative model, enabling it to produce responses that are not only factually correct but also contextually appropriate. The paper emphasizes the importance of such a system in the context of mental health and suicide prevention, where timely and accurate information can be lifesaving. Their research and model contributed to the field by offering a potential solution to bridge the gap between the vast amount of information available and the specific needs of individuals seeking help. The system's design is grounded in the latest advancements in artificial intelligence and machine learning, promising to enhance the capabilities of existing digital platforms in providing support for suicide prevention. The authors' work is a significant step towards harnessing technology to address complex health challenges and improve outcomes in public health domains.

Ovadia et al. (2023) compared two prevalent methods for enhancing the knowledge base of large language models (LLMs): unsupervised fine-tuning and retrieval-augmented generation (RAG). The study scrutinized the efficacy of these approaches across various knowledge-intensive tasks and domains. The study revealed that while unsupervised fine-tuning can lead to some improvements, RAG consistently surpasses it in performance. This is true for both knowledge previously encountered during the training of the LLMs and entirely new information. The authors also discovered that LLMs face challenges in assimilating new factual data through unsupervised fine-tuning. However, they found this can be mitigated by exposing the models to multiple variations of the same fact during the training phase. This research contributed to the understanding of how LLMs can be adapted to incorporate new knowledge and refine their existing capabilities, which is crucial for their application in dynamic and specialized fields.

Ren, Guo, Xu, and Xiao (2023) presented a framework for generating guided more diverse and human-like questions, which is a significant contribution to the field of natural language processing. The authors propose a three-stage process: retrieve, generate, and rerank, to produce questions that closely mimic the way humans inquire. Initially, the framework retrieves relevant information from a vast dataset, ensuring that the generated questions are grounded in factual content. Subsequently, the generation phase employs advanced language models to formulate coherent and contextually appropriate questions. Finally, the reranking stage evaluates the questions, prioritizing those that most effectively reflect human curiosity and information-seeking behavior. Their method not only streamlines the question generation process but also enhances the quality of the questions produced, making them more useful for applications such as virtual assistants and educational tools. The paper's findings indicate that this approach can significantly improve the relevance and human-likeness of generated questions, marking a step forward in the development of intelligent systems capable of engaging in meaningful dialogue.

Ahn, Lee, Shim, and Park (2022) introduced a retrieval-augmented response generation model designed for knowledge-grounded conversations. Their model was distinct in its ability to retrieve a range of documents relevant to both the topic and local context of a conversation, which it then uses to generate informed responses. Unlike previous models that focused on single documents or disregarded the conversation topic, this approach considers multiple representations derived from both the conversation's topic words and the tokens preceding the response. Their model's innovative data-weighting scheme is noteworthy as it encourages the generation of knowledgeable responses without relying on ground truth knowledge. The authors' evaluations, both automatic and human, indicate that their model outperforms state-of-the-art models in generating responses that are more knowledgeable, diverse, and contextually relevant.

Zhang, Xiao, Liu, Dou, and Nie (2023) was interested in addressing the challenges faced by large language models (LLMs) due to their inherent limitations in knowledge, memory, alignment, and action. The authors argued that these limitations cannot be overcome by LLMs alone and proposed a novel approach they called the LLM-Embedder. This approach aims to support the diverse retrieval augmentation needs of LLMs through a unified embedding model. The LLM-Embedder is designed to handle various retrieval tasks that capture distinct semantic relationships, which are often subject to mutual interference. The paper details a systematic optimization of the training methodology for the LLM-Embedder, including reward formulation based on LLMs' feedback, stabilization of knowledge distillation, multi-task fine-tuning with explicit instructions, and homogeneous in-batch negative sampling. These strategies have led to the LLM-Embedder outperforming both general-purpose and task-specific retrievers in various evaluation scenarios. The authors have made their checkpoint and source code publicly available, contributing to the field of information retrieval and the enhancement of LLMs' capabilities.

Feng, Feng, Zhao, Yang, and Qin (2024) proposed an innovative approach to augmenting large language models (LLMs) through a retrieval-generation synergy. Their method sought the challenge of obtaining effective documents for knowledge-intensive tasks. Traditional methods rely on either retrieving information from an external knowledge base or generating documents directly from LLMs. The authors proposed an iterative retrieval-generation collaborative framework that leverages both parametric (inherent model knowledge) and non-parametric (external databases) knowledge sources. This synergy allows the model to find the correct reasoning path, which is crucial for multi-step reasoning tasks. The framework, named ITRG (Iterative Retrieval-Generation), consists of two steps: generation augmented retrieval (GAR) and retrieval augmented generation (RAG). In GAR, the model expands queries with pseudo-documents generated by LLMs, while in RAG, it uses retrieved documents to inform further document generation. They report empirical results from experiments on four question answering datasets, including single-hop and multi-hop QA tasks, showing that ITRG significantly improves the reasoning abilities of LLMs and outperforms previous baselines.

3. METHODS

This section will discuss the methods used for the implementation of the RAG application. The methods selected and used in this paper were based on those that were felt would produce the most optimum results for healthcare related prompts.

Design Overview

The proposed RAG system consists of a language model (Llama), a retrieval system and a chatbot. Amazon bedrock is a platform containing several foundation models that can be utilized in designing Gen AI applications.

The retrieval system and chatbot are designed using python programming language. Using Langchain library, we import bedrock and bedrock embeddings from the Amazon bedrock cloud service. We use AWS CLI (Command line interface) to interact with AWS services using commands.

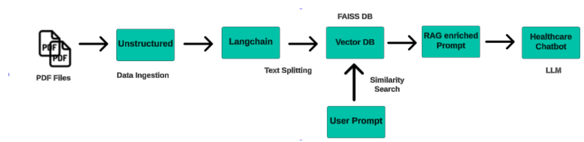

Figure 4: RAG Architecture

Figure 4 illustrates our RAG architecture and how it involves ingesting our dataset into the system as unstructured data, the domain specific data which is in the form of PDF files is gotten from reliable healthcare sources such as cdc.gov, cancer.gov and so on.

Using Langchain, a python library for importing LLMs from Amazon bedrock, we split the text in the PDF files and store them as vector embeddings in the FAISS database. For user prompts, a similarity search is done based on the vector embeddings in the vector store and a response that is augmented with specific healthcare information is provided. The data to be augmented into the foundation LLM is ingested into the application using a PyPDF loader function from Langchain. The text in the documents is then split using a text splitter (Recursive character splitter).

We accessed the Llama 2 foundation model and our vector embedding (Amazon Titan embedding) using access keys as retrieved from Amazon bedrock cloud service. A secret access key and an access key is provided for validation by our RAG application using the AWS command line interface and is illustrated in Figure 5.

To address the identified gaps in the literature, specifically the need for more robust models capable of handling research related to LLMs or base foundation models, fine-tuning and retrieval augmented generation all in one suite, we employed the use of Amazon bedrock, an AWS cloud service known for its performance in such use cases.

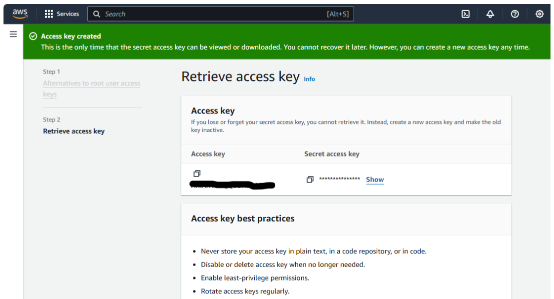

Figure 5: Retrieving access keys on AWS bedrock

We used Streamlit for our user-facing chatbot that provided answers to healthcare related prompts. Figure 6 shows the sample code for the prompt template, and Figure 7 shows the code for Streamlit chatbot.

```
prompt_template = """

Human: Use the following pieces of context to provide a
concise answer to the question at the end using at least 250 words to summarize
with detailed explantions. If you don't know the answer,
just say that you don't know, don't try to make up an answer.
<context>
{context}
</context>

Question: {question}

Assistant:"""

PROMPT = PromptTemplate(
    template=prompt_template, input_variables=["context", "question"]
)

def get_response_llm(llm,vectorstore_faiss,query):
    qa = RetrievalQA.from_chain_type(
    llm=llm,
    chain_type="stuff",
    retriever=vectorstore_faiss.as_retriever(
        search_type="similarity", search_kwargs={"k": 3}
    ),
    return_source_documents=True,
    chain_type_kwargs={"prompt": PROMPT}
)
    answer=qa({"query":query})
    return answer['result']
```

Figure 6: Sample code for Prompt template

```
def main():
    st.set_page_config("Chat PDF")

    st.header("Amazon Bedrock Titan Chat")

    user_question = st.text_input("Ask a Question")

    with st.sidebar:
        st.title("Update Or Create Vector Store:")

        if st.button("Vectors Update"):
            with st.spinner("Processing..."):
                docs = data_ingestion()
                get_vector_store(docs)
                st.success("Done")

    if st.button("Titan Output"):
        with st.spinner("Processing..."):
            faiss_index = FAISS.load_local("faiss_index", bedrock_embeddings)
            llm=get_titan_llm()


            st.write(get_response_llm(llm,faiss_index,user_question))
            st.success("Done")

if __name__ == "__main__":
    main()
```

Figure 7: Sample and Streamlit chatbot

Evaluation metrics

To evaluate the quality of our responses in comparison to other base LLMs, we employed some evaluation techniques that measure automatically generated responses versus a set of reference(s). Consequently, we utilized **"ROUGE"** and **"METEOR"** as evaluation metrics and **"WikiMed"** as our reference or "ground truth". WikiMed is the largest encyclopedia for medical and health related articles.

ROUGE- Recall-oriented understudy for gisting evaluation; measures the overlap of unigrams (single words) between the system summary and reference summary.

$$Recall = \frac{Number\ of\ overlapping\ unigrams}{Total\ number\ of\ unigrams\ in\ reference}$$

METEOR- Metric for Evaluation of Translation with Explicit Ordering; is a metric used for evaluating machine translation output. It calculates the similarity between the system output and the reference translations.

$$Recall = \frac{m}{Wr}$$

Human evaluation is also a valid evaluation technique despite the subjective nature of it. Experts in the medical field such as doctors, psychologists, physicians can evaluate the quality of the automatically generated text (RAG response) and rate it versus the base model outputs.

The decision to use rouge and meteor for our evaluation stems from their efficacy in accurately calculating similarities between machine generated outputs, coupled with their lack of use in the literature studied, with other researchers preferring to use human evaluation, cosine similarity or other F1 measurements. Ascorbe et al. (2023)

In this research, we have opted to use the Rouge and Meteor metrics for evaluation, however, there are other metrics that can be applied to evaluate the quality of the machine generated output/response.

4. RESULTS

To evaluate the quality of the response generated by the RAG chatbot (Augmented Llama model), we compare it with chat GPT 3.5 and a base Llama model.

Using multiple short prompts relating to chronic diseases such as; **What is Hepatitis? What is Diabetes? What is Tuberculosis?** etc. The responses are evaluated against a reference text gotten from "WikiMed".

Three scenarios were tested using responses less than 250 characters response, more than 250 characters response and a combination of more than one LLM response.

Using the "**Rouge 1**" and "**Meteor**" metrics, the results show that;

-**Augmented Llama model** outperforms other models using Rouge 1 and < 250 characters

-**Chat GPT 3.5** outperforms other models using Rouge 1, Meteor and > 250 characters

-**Base Llama model** outperforms other models using Meteor and with <250 characters

However, the results considerably improved when we combined two models and evaluated it against the reference output.

LLM	ROUGE 1	METEOR
ChatGPT 3.5 model	0.28	0.21
Augmented Llama model	**0.34**	0.23
Base Llama model	0.28	**0.24**

Table 1: LLM responses < 250 characters

LLM	ROUGE 1	METEOR
ChatGPT 3.5 model	**0.44**	**0.26**
Augmented Llama model	0.42	0.23
Base Llama model	0.41	0.18

Table 2: LLM responses >250 characters

LLM	ROUGE 1	METEOR
ChatGPT 3.5 model + Augmented Llama	**0.47**	**0.35**
Chat GPT 3.5 model	0.44	0.26
Augmented Llama model	0.42	0.23
Base Llama model	0.41	0.24

Table 3: LLM combined responses vs standalone responses

Table 1. shows that for responses smaller than 250 characters, the augmented llama and chat GPT models perform well using the rouge and meteor evaluation metrics respectively. Table 2. On the other hand, has chat GPT outperforming the augmented llama model for responses greater than 250 characters on both rouge and meteor measures. These results lead us to believe that with a larger character count, the chat GPT LLM outperforms the augmented llama model. However, as seen in Table 3. We record a 7% and 35% increase in the rouge and meteor scores respectively, when we combine responses from both LLMs.

In comparison with studies done by Zhu et al. (2020), with a larger corpus the model performance improves but starts to decline after the corpus surpasses 1M characters (query and response). Previous research also shows a positive correlation between the evaluation metric BLEU and human evaluation.

Furthermore, these results provide answers to our research questions.

RQ1- Our results show that retrieval augmented generation reduces hallucination of LLMs.

RQ2- The combination of LLM responses provided an improvement in our evaluation scores using Rouge and Meteor with a 7% and 35% increase respectively.

5. CONCLUSON

The research goal of this study is to create a RAG chatbot using Gen AI and cloud services to further the scarce research around healthcare chatbots and/or virtual assistants and improve hallucination challenges in LLMs for healthcare related prompts.

Our study shows the potential of using RAG systems for healthcare chatbots in terms of improving accuracy of the responses generated by these chatbots. Augmenting the base LLM models with external healthcare data improves the information available to individuals and enhances their access to healthcare knowledge.

While this study exposes a viable use-case for RAG-based LLMs in the healthcare domain, there are some limitations to the study. The small and limited dataset used for this study leaves room for limited generalizability and higher chances of statistical anomalies. Another limitation also lies in the fact that our study only makes use of three LLMs.

Future work can go a step further by carrying out similar research using other languages and for individuals without access to or bad internet who need accurate healthcare information. Larger datasets and the use of other LLMs can also be studied in the future.

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APPENDIX

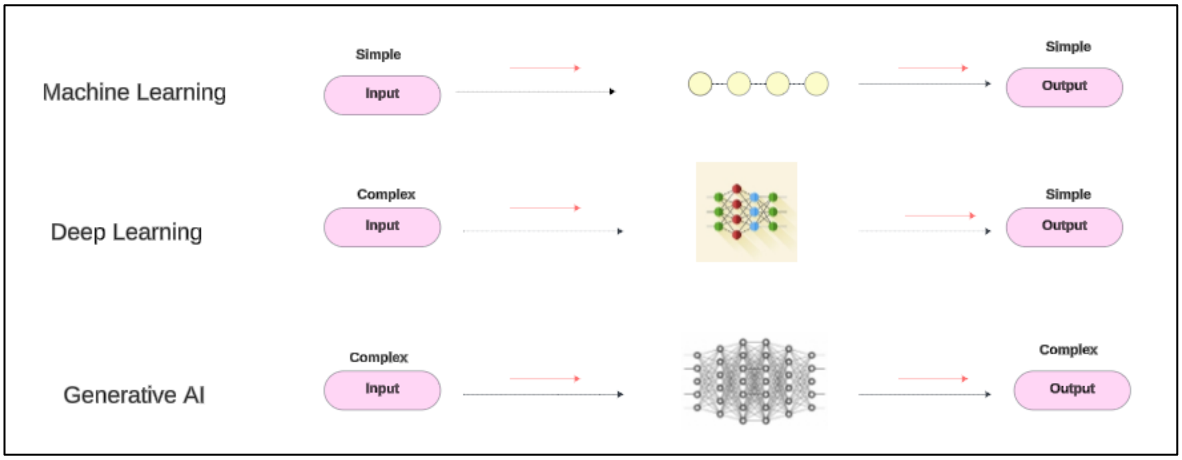

Figure 1: ML, DL, and Gen AI data flow comparison

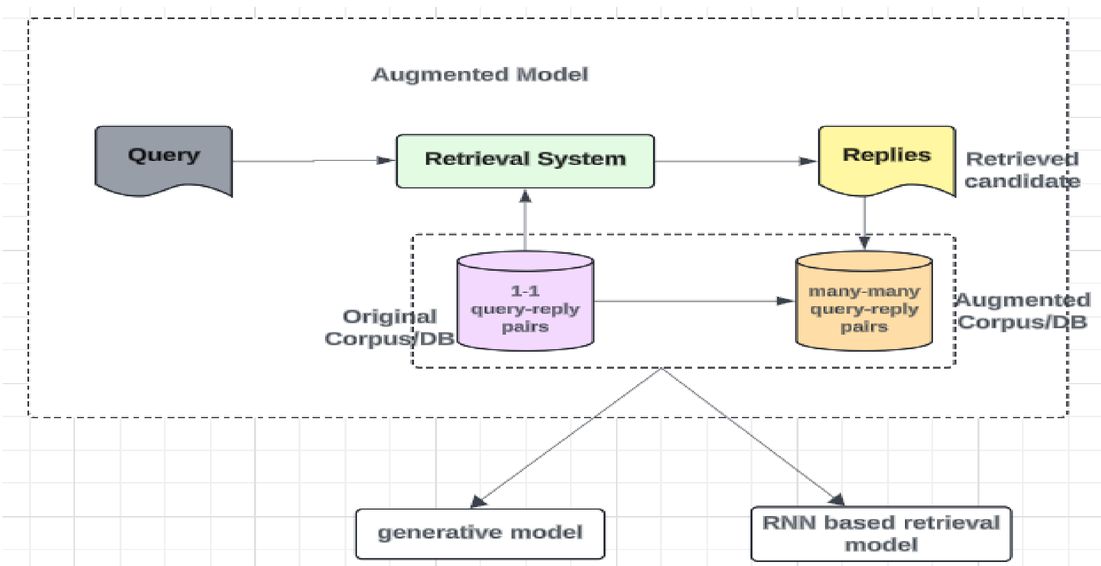

Figure 2: Dialog system for RAG application

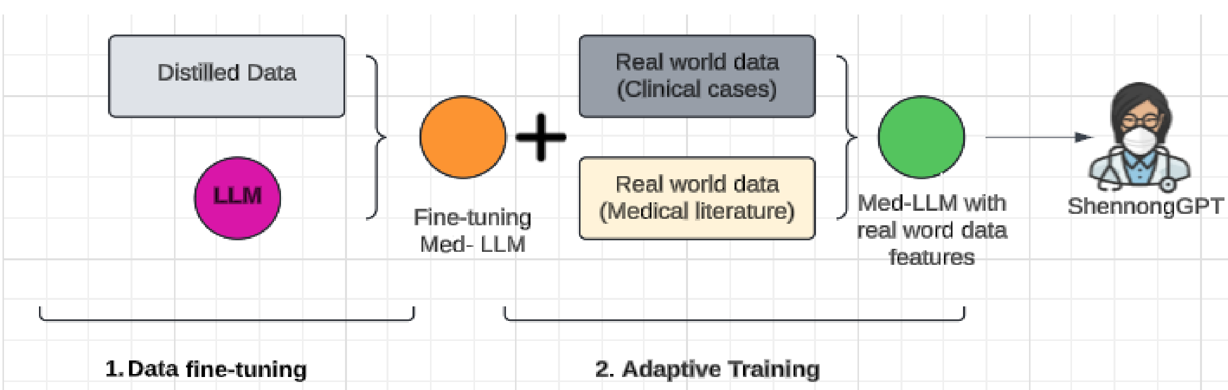

Figure 3: ShennonGPT architecture

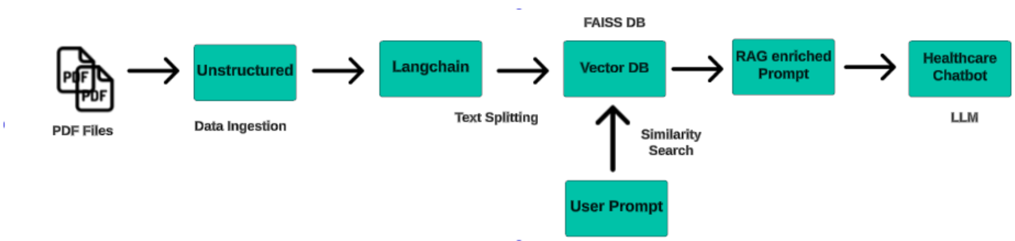

Figure 4: RAG Architecture

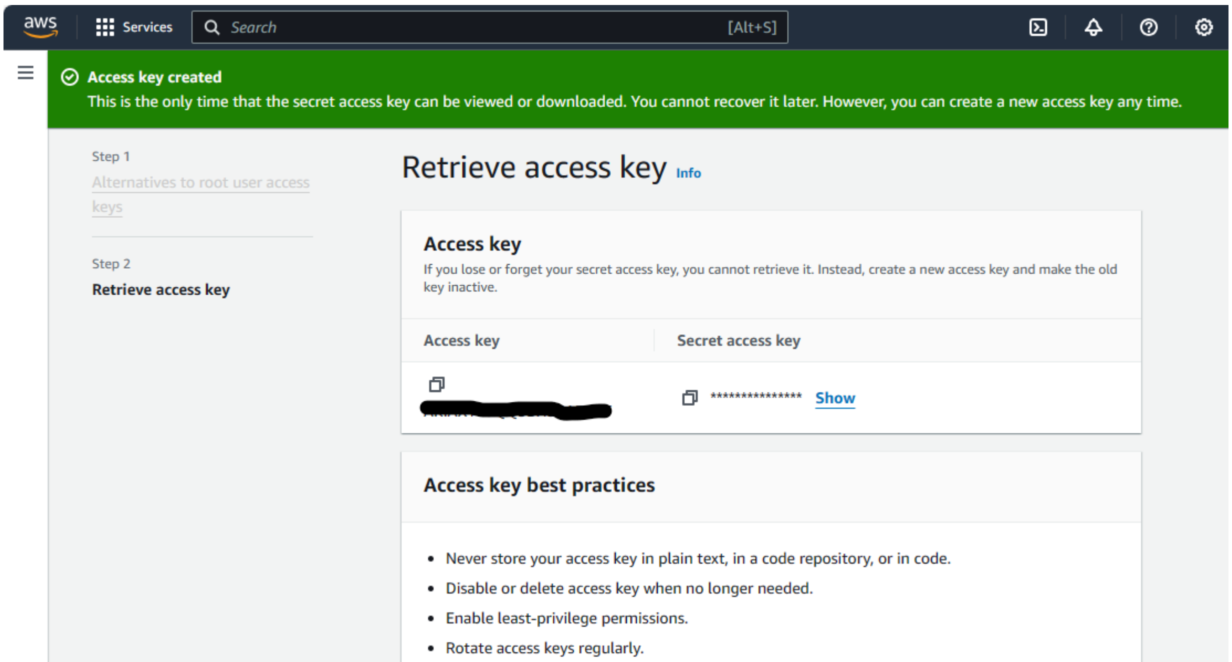

Figure 5: Retrieving access keys on AWS bedrock

```
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concise answer to the question at the end using at least 250 words to summarize
with detailed explantions. If you don't know the answer,
just say that you don't know, don't try to make up an answer.
<context>
{context}
</context>

Question: {question}

Assistant:"""

PROMPT = PromptTemplate(
    template=prompt_template, input_variables=["context", "question"]
)

def get_response_llm(llm,vectorstore_faiss,query):
    qa = RetrievalQA.from_chain_type(
    llm=llm,
    chain_type="stuff",
    retriever=vectorstore_faiss.as_retriever(
        search_type="similarity", search_kwargs={"k": 3}
    ),
    return_source_documents=True,
    chain_type_kwargs={"prompt": PROMPT}
)
    answer=qa({"query":query})
    return answer['result']
```

Figure 6: Sample code for Prompt template

```
def main():
    st.set_page_config("Chat PDF")

    st.header("Amazon Bedrock Titan Chat")

    user_question = st.text_input("Ask a Question")

    with st.sidebar:
        st.title("Update Or Create Vector Store:")

        if st.button("Vectors Update"):
            with st.spinner("Processing..."):
                docs = data_ingestion()
                get_vector_store(docs)
                st.success("Done")

    if st.button("Titan Output"):
        with st.spinner("Processing..."):
            faiss_index = FAISS.load_local("faiss_index", bedrock_embeddings)
            llm=get_titan_llm()


            st.write(get_response_llm(llm,faiss_index,user_question))
            st.success("Done")

if __name__ == "__main__":
    main()
```

Figure 7: Sample and Streamlit chatbot

Thirty-time Speed-up for Course Selecting by Using the Power of Machine

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Abstract

In the demanding environment of academic advising, faculty members face the significant challenge of assisting students with course selection and graduation planning within a tight timeframe. This paper presents a novel application of automation technology, termed Auto-Course Selection, which dramatically accelerates this process. Traditionally, constructing a tailored, error-free course and graduation plan for each student requires approximately 15 minutes, excluding further communications. The Auto-Course Selection system reduces this time to an impressive 30 seconds per student by automating the evaluation of prerequisites, checking course availability, resolving scheduling conflicts, and ensuring alignment with graduation timelines. This study details the development and operational deployment of the system, emphasizing the methodology for data acquisition, the architecture of the data structures, the logic underpinning the course recommendation algorithm, and the overall feasibility of the project. Our results indicate a thirty-fold increase in efficiency, providing a scalable and reliable solution that substantially eases the advising burden on faculty, particularly those managing large cohorts, and minimizes the potential for human error.

Keywords: Academic Advising, Course Selection, Automation, Data Acquisition, System Deployment, Educational Technology, Efficiency Improvement.

Recommended Citation Li, Z., Yuan, J., Nobel, A., (2025). Thirty-time Speed-up for Course Selecting by Using the Power of Machine. *Journal of Information Systems Applied Research and Analytics*. v18, n3 pp 30-43. DOI# https://doi.org/10.62273/JOQP7724

Thirty-time Speed-up for Course Selecting by Using the Power of Machine

Zhouzhou Li, Juefel Yuan and Ashikur Rahman Nobel

1. INTRODUCTION

In the realm of academic advising, one of the perennial challenges faced by faculty members is the efficient and accurate selection of courses and planning of graduation timelines for students (Algarni et al., 2023; Gong et al., 2024). This process, traditionally manual and time-consuming, is crucial to ensuring that students meet their academic requirements and achieve their educational goals within the stipulated time frame. Appendix A demonstrates the manual approach. However, it often results in significant time expenditure and a high potential for human error, especially when dealing with large cohorts of students.

With the rapid advancements in technology, particularly in the fields of software development and automation (Li et al., 2024; Mirzaolimovich et al., 2023), there exists an opportunity to revolutionize the way academic advising is conducted. This paper introduces Auto-Course Selection, an innovative system designed to streamline and expedite the course selection process through enhanced automation techniques. By automating key tasks such as evaluating prerequisites, checking course availability, resolving scheduling conflicts, and aligning course selections with graduation timelines, this system can reduce the time required for these tasks from an average of 15 minutes to just 30 seconds per student.

The development and deployment of the Auto-Course Selection system represent a significant advancement in educational technology (Atalla et al., 2023; Maphosa et al., 2023). This system not only enhances efficiency but also ensures a higher degree of accuracy in the advising process. By minimizing human intervention, the potential for errors is drastically reduced, providing a more reliable and scalable solution for academic institutions.

This paper provides a comprehensive overview of two Auto-Course Selection systems (Python-based and Web-based), detailing their development process, data acquisition methodologies, data architecture, and the logic behind their course recommendation algorithms. Our study demonstrates the systems' feasibility and effectiveness, highlighting a thirty-fold increase in efficiency. This significant improvement underscores the systems' potential to ease the advising burden on faculty members, particularly those managing large student populations and to enhance the overall academic experience for students.

The subsequent sections of this paper are structured in the following manner. In the 'Literature Review' section, we review the benefits and importance of auto-course selection. In the 'Methods' section, we describe the data acquisition techniques, data sources, and course recommendation logic in the Auto-Course Selection system, supported by visual workflows and examples from the Southeast Missouri State University (SEMO) course enrollment systems. In the 'Experimental Results and Analysis' section presents the details and outcomes of the web-based and Python-based auto course selection systems. The 'Conclusions and Future Work' section will offer a wrap-up of the findings and shed light on potential avenues for future research.

2. LITERATURE REVIEW

The benefits of auto-course selection are numerous, and research in this area is ongoing. One study published in the Applied Information Technology and Computer Science journal developed a Course Selection Guidance System (CSGS) (Zaidi et al., 2023). CSGS is a web-based tool developed to aid Form 5 students in selecting diploma courses at University Tun Hussein Onn Malaysia (UTHM) and University Putra Malaysia (UPM), tailored to their personality types and academic results. Utilizing Holland's Theory for personality assessment and developed with HTML, JavaScript, PHP, and SQL, the CSGS undergoes alpha and beta testing to optimize user experience. However, the CSGS system cannot be widely used by other universities.

Another study published in the Applied Mathematics and Nonlinear Sciences presents a teaching information management system that utilizes a nonlinear differential equation approach, specifically the Riccati differential equations with statistical linearization, to optimize the college course selection process. The system employs collaborative filtering based on nonlinear differentiation and student feature classification, and experiments have shown it to be correct in recommending courses 34.6% of the time. It concludes by emphasizing the system's potential to enhance teaching resource allocation and provide optimal elective plans, contributing to the development of "intelligent campus" and "humanization" in education within Chinese universities (Yangg et al., 2023). Nonetheless, the system's application range is overly broad, and its course selection accuracy remains limited.

The third study, published in the International Conference on Modern Education and Information Management developed a hybrid recommendation algorithm for a university course selection system designed to provide intelligent course recommendations based on relationships among students and between students and courses. The paper explores the development of a recommendation system that combines collaborative filtering with content-based techniques by utilizing both explicit and implicit student data. The findings indicate that the algorithm effectively addresses the randomness and lack of direction in student course selection, ensuring a better alignment of students' learning abilities with course demands (Luxiao et al., 2022). However, this system focuses more on establishing relationships between courses rather than helping students choose courses.

In conclusion, while various systems have been developed to enhance the process of course selection, each exhibits unique strengths and limitations. Systems like CSGS offer tailored recommendations but lack broader applicability across different institutions. Meanwhile, approaches using complex models like Riccati differential equations provide innovative solutions but may suffer from broad applicability and lower accuracy issues. On the other hand, hybrid recommendation systems show promise in aligning student capabilities with course demands, though they might prioritize relational data over direct course selection assistance. The ongoing evolution in this field suggests a move towards more integrated, adaptable, and student-centric course selection technologies that can potentially transform academic advising across diverse educational landscapes.

3. Methods

This section explains the implementation and deployment process of the Auto-Course Selection research project by utilizing two ways: 1) Web-based auto-course selection with *html* and *JavaScript*. 2) Python-based auto-course selection with *re* and *subprocess* modules. The primary focus are the sources of information, data acquisition - techniques and feasibility, data structure building, course recommendation logic and deployment. Appendix B shows the base workflow for auto-course selection.

Problem and Objective: To automate and speed up the course advising task for academic advisors is the primary goal here. Organized information extraction from relevant sources is an addition to this objective.

The data collection and experimental procedures detailed in this paper utilize information from the Department of Computer Science at SEMO course enrollment webpage. The methodology employed is thorough and widely applicable, as the majority of university course enrollment systems globally are web-based. This approach ensures that the findings are relevant and can be generalized to similar systems at other institutions.

Data Information Sources

The required information is split into three sets:

1. Pre- and Co- Requisite information: from SEMO Course Bulletin (SEMO BULLETIN, 2024)
2. Offered Courses (per semester): Look-up Classes
3. DegreeWorks (per student): SEMO DegreeWorks (SEMO DEGREEWORKS, 2024)

Pre- and Co-Requisite information: from SEMO Course Bulletin, which is publicly available information acquired directly by fetching the page. Offered Courses (per semester): Look-up Classes are to be copied and pasted by each client/student into a webpage field. DegreeWorks (per student): SEMO DegreeWorks is to be copy-pasted by each client/student. Appendix C visualizes the data format across the sources.

Data Acquisition Techniques

SEMO Course Bulletin: This section is to be fetched while loading the client-side web page/app.

The client-sided solution makes one single PHP call to fetch the page from the server, as shown in Appendix D.
Look-up classes:
Here is the process of providing information of Look-up classes to the client-side tool:

1. Under look-up classes tool in my.semo.edu, pick the specific semester.
2. Then choose 'Advanced Search' at the end of the page,
3. In the 'Advanced Search' page pick all of the department options by clicking the top and scrolling to the bottom and shift+click the bottom option,
4. Click search, in this search page, click anywhere, then do Ctrl+A and Ctrl+C (copy all),
5. Lastly, go to the tool page and paste it into the Look-up classes box.

Degreeworks: Same as above, but click inside the Degreeworks window before copying everything and pasting it into the Degreeworks section/textbox of the tool.

3. Experimental Results and Analysis

Web-based Auto Course Selection
Information Extraction:
The three sets of information are extracted using 'regular expression' (Regular Expression, 2024), 'jQuery' (JQuery, 2024) and vanilla JavaScript codes. The end results are the following data structures:

- scrapedPrereqData: JavaScript dictionary with the course codes as 'key' and list of prerequisites as 'value'.
- scrapedCoreqData: same as above but for co-requisites.
- offered courses: JavaScript dictionary with the course codes as 'key' and time - course name - days as 'value'.
- completed courses: JavaScript dictionary with the completed course codes as 'key' and true as 'value' (for easy and fast access).
- remaining courses: JavaScript dictionary with the 'not yet completed' course codes as 'key' and true as 'value' (for easy and fast access).
-

The aforementioned set of information would suffice in generating course selection.

Course Recommendation Logic:
The steps follow:

1. Remove all completed courses from remaining list (Completed courses end up with remaining ones due to Degreeworks formatting)
2. Only keep remaining courses in the list if it's offered in the semester
3. On each remaining courses, then, check if the pre-requisites are "None"
   - If "None", push the course to 'recommendation list'
   - Else, start checking for pre-requisites - if they are completed or not (also account for special cases - like consent of instructor/chairperson)
     - If the pre-requisites are completed (checked on each individual groups - if any group is completed) - push course into 'recommendation list', add note for special cases
     - If incomplete, do nothing
4. For each remaining course, check for co-requisites in the same way. If a course that is already in the recommendation list appears as a co-requisite, then also add the current course to the 'recommendation list' (based on the co-requisite condition)
5. Process the 'recommendation list' for final output (to make it look better)

Deployment:
Because the deployment involves a single PHP function call, installing PHP on the server side is necessary. The application is designed to be browser-friendly and features a minimalistic user interface. Therefore, the following server-side requirements are essential for deployment (No special configuration required, can be customized as needed):

1. Apache or equivalent web server
2. PHP to work alongside the web server

On the client side, all processes except data acquisition are automated, which includes generating recommendations and retrieving the bulletin without user intervention. The sole significant external resource on the client side is 'jQuery', which is sourced from the Google Web Hosted Library (Google Hosted Libraries, 2024).

Open Worldwide Application Security Project (OWASP) and Zed Attack Proxy (ZAP) testing:

Initial testing for this project was conducted using the security tool - Owasp Zap (Owasp Zap, 2024), to identify usable segments of the

data sources. For this purpose, a collection of standalone scripts was developed, mirroring the workflow of the primary client-side solution.
After importing the scripts into the Standalone section of the Zap Scripts, the pages (Degreeworks, Course Bulletin, Look-up Classes) need to be loaded into the proxy history, then all scripts except the ’main’ script needs to be run first and then lastly, the ’main’ script needs to be executed. The result will be the recommended course list shown in the ’console’ display tab. Appendix E displays the interface of the web-based auto course selection system, while Appendix F illustrates the email content automatically generated by this system, which will be sent to students advising them on which courses to enroll in for the upcoming semester.

Python-based Auto Course Selection
Information Extraction:
The three sets of information are obtained utilizing ’re’ (Python re Module, 2024) and ’subprocess’ (Python subprocess Module, 2024) modules in Python:

- ’re’ module: parsing and extracting relevant information from text data, such as course codes, prerequisites, or availability from online catalogs or web pages. In addition, validating user inputs, like ensuring course codes or identifiers match a specific format before processing.
- ’subprocess’ module: Interacting with system-level scripts that might be part of the course selection infrastructure, like scripts for database updates, enrollment processes, or integration with other institutional software. In addition, automating tasks require external commands or applications, such as data backups or system checks related to course selection systems.

The steps follow:

1. Use the ’re’ to scrape and parse course information from the university’s course catalog web pages. Regular expressions can help in extracting structured data like course names, numbers, prerequisites, and descriptions.
2. Before allowing a teacher/student to select courses, use ’re’ to ensure that their inputs (like course codes or names) match the expected patterns, thus avoiding errors during the selection process.
3. Use the ’subprocess’ module to execute the command directly from the code. Refer to Figure 1 for the specific command.
4. After the courses are selected, an email to the student will be automatically generated and prepared for sending. Appendix G provides an example of the generated email.

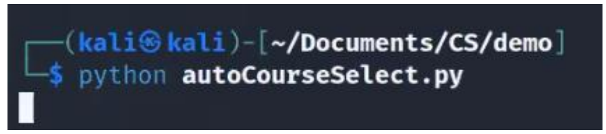

Figure 1: Run Command to Execute Auto Course Selection System.

By combining these two powerful modules in Python, we can create a robust system that automates the process of course selection for students, ensuring efficiency and accuracy while interacting with existing university systems. These web-based and python-based auto course selection systems speed up the course selection advising and reduce the course selection time from 15 minutes to 30 seconds for each student. We inserted code to print out the timestamp when the tool starts to handle a student’s data, and print out another timestamp when the tool completes the course selection for the student by generating the advising email. The difference between the two timestamps will be the time consumption of course selection per student. In 99.99% cases, the time consumption is less than 5s a student. The declared ‘30’ seconds are a conservative number. Also, we would like to point out that we did not use a dedicated machine to host the tool. We simply allocated a Kali Linux VM with a 30 GB storage, 4 GB RAM, and two cores from a DELL laptop (11th Gen Intel(R) Core(TM) i5-1145G7 @ 2.60GHz 1.50 GHz, 16 GB RAM, Windows 11 Education 23H2) to run this tool. Therefore, 30 seconds are a very conservative number. Regarding the time consumption in traditional manual course selection, it is calculated from the fact that faculty reserve a 15-minute meeting per advisee for their course selection.

4. CONCLUSIONS AND FUTURE WORK

In this study, we introduced the Auto-Course Selection system, leveraging the capabilities of machine learning and automation to significantly enhance the efficiency of academic advising. By automating the critical aspects of course selection, including prerequisite evaluation, course availability checks, scheduling conflict resolution, and alignment with graduation timelines, our system reduces the advising time per student from 15 minutes to just 30 seconds. This thirty-fold increase in efficiency not only eases the workload of faculty advisors but also ensures greater accuracy and consistency in the advising process.

The deployment of both web-based and Python-based implementations demonstrates the system's versatility and robustness in interacting with existing university infrastructures. The detailed methodology for data acquisition, the architectural design of data structures, and the underlying logic of the course recommendation algorithm collectively highlight the system's comprehensive approach.

Our experimental results confirm the significant impact of the Auto-Course Selection system, providing a scalable, reliable, and error-minimizing solution for academic institutions. This innovation holds the potential to transform academic advising, allowing faculty to manage larger cohorts with reduced effort and increased precision, ultimately benefiting both advisors and students. As universities continue to seek efficient and effective solutions to meet the growing demands of academic advising, the Auto-Course Selection system represents a pioneering advancement in educational technology.

Looking ahead, there are several avenues for expanding and enhancing the Auto Course Selection system. A key area for improvement involves integrating advanced machine learning techniques. Universities offer a wide range of elective courses, both within and across different departments. By allowing students to input their research interests or career goals, the system could analyze the patterns and content of available elective courses. Consequently, it could provide personalized recommendations, suggesting the elective courses that best align with each student's individual interests and aspirations. This enhancement would not only optimize course selection but also help students make more informed decisions, ultimately supporting their academic and professional development.

Another essential aspect for future work is the improvement of the universities' curriculum. For example, by analyzing enrollment patterns and trends, machine learning can forecast demand for specific courses, helping universities to optimize course offerings and allocate resources effectively. In addition, machine learning can identify gaps in the current curriculum by comparing it with industry trends, job market requirements, and student feedback. This can inform the development of new courses or the revision of existing ones.

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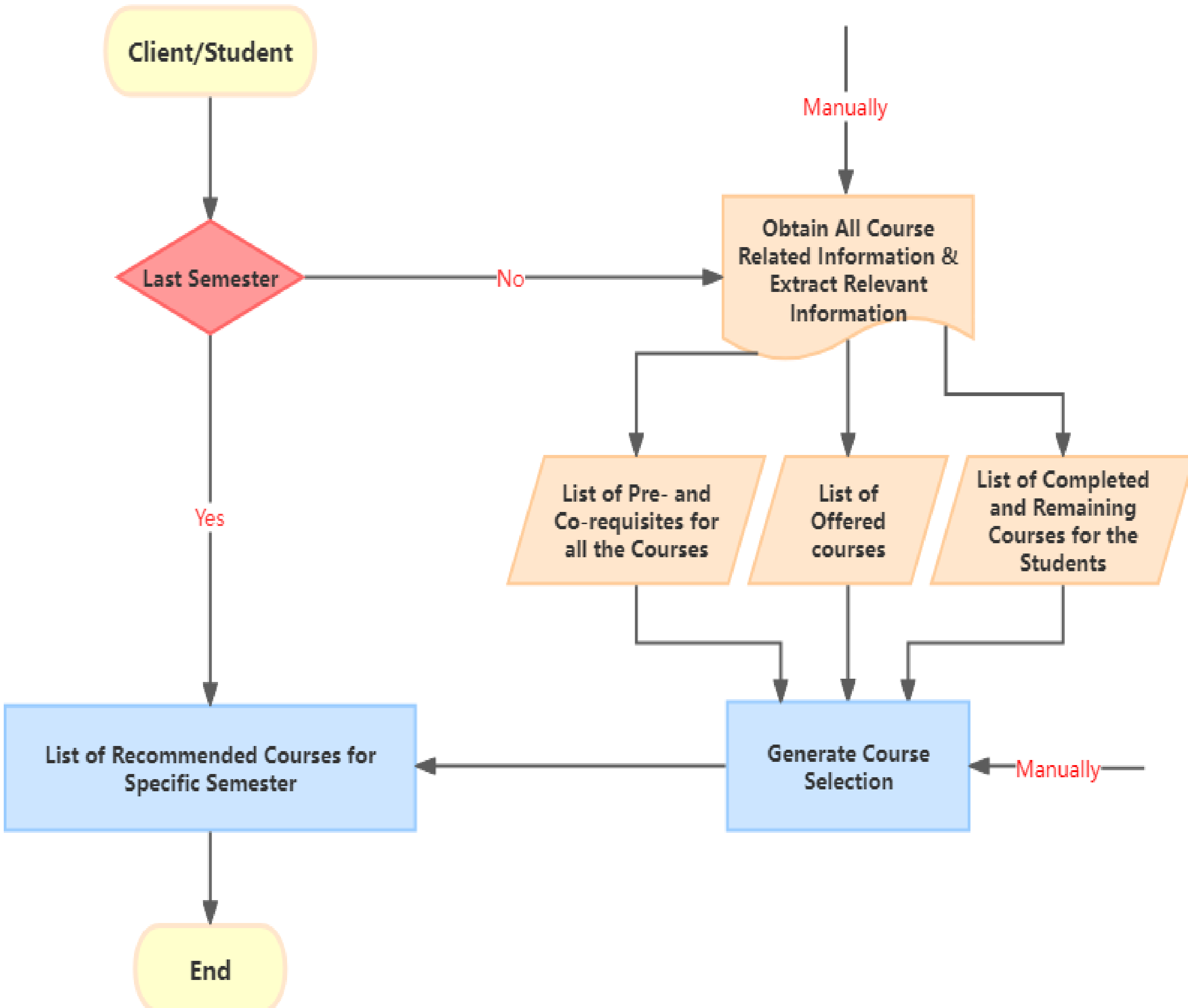
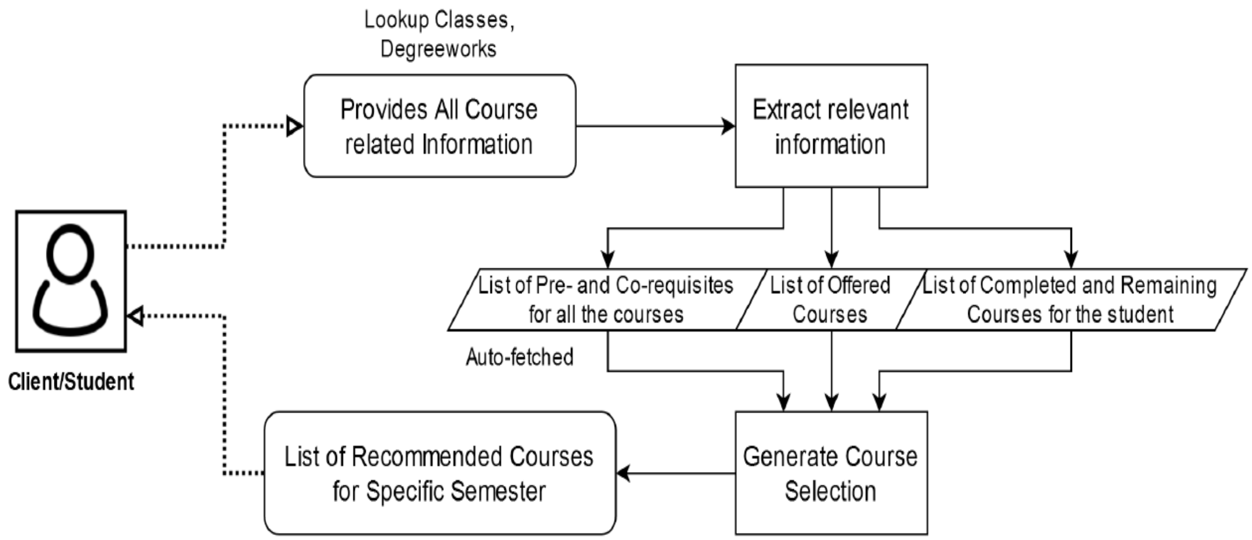
APPENDIX A

Manual Approach Course Selection



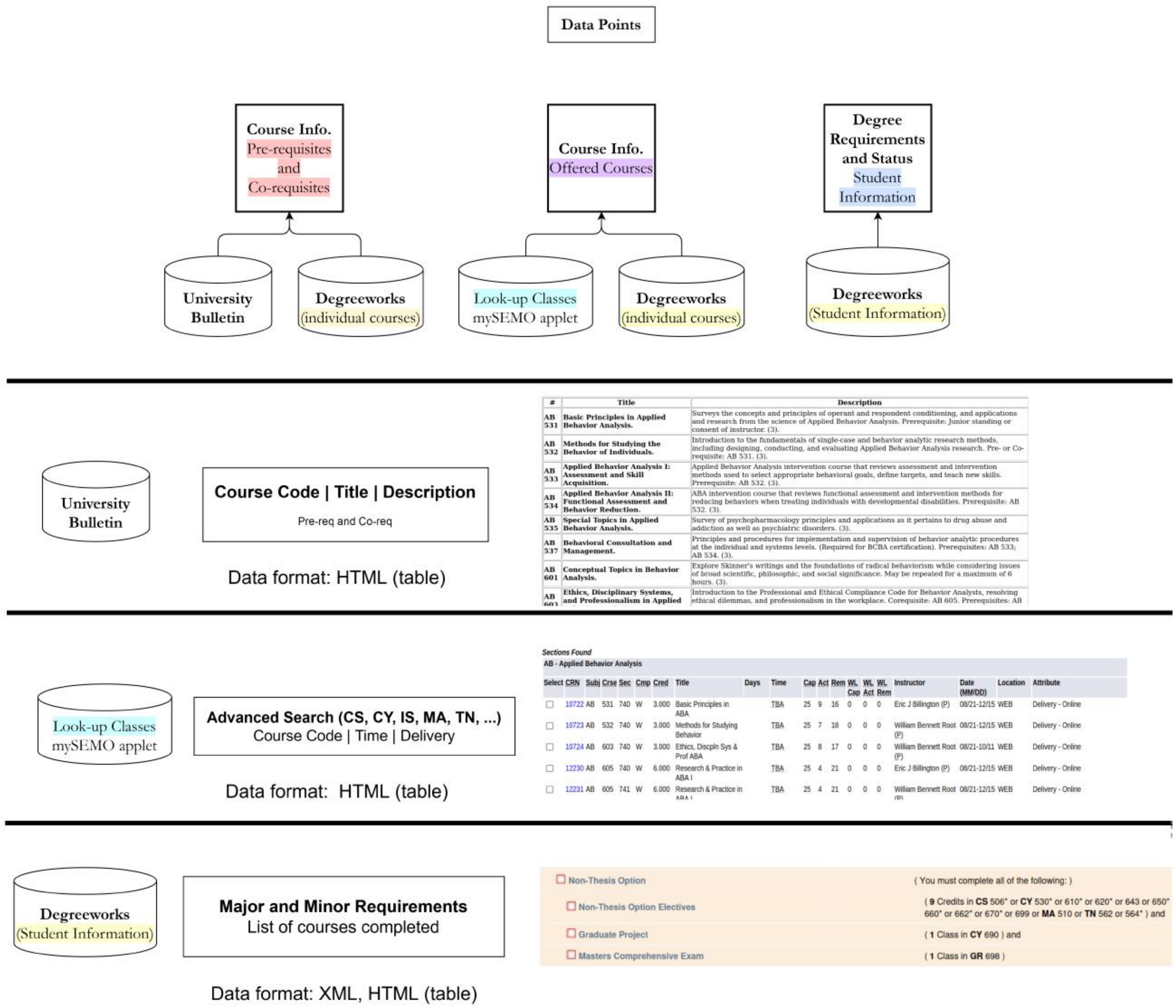
APPENDIX B

Base workflow: Auto-Course Selection



APPENDIX C

Data Sources: Auto-Course Selection



APPENDIX D

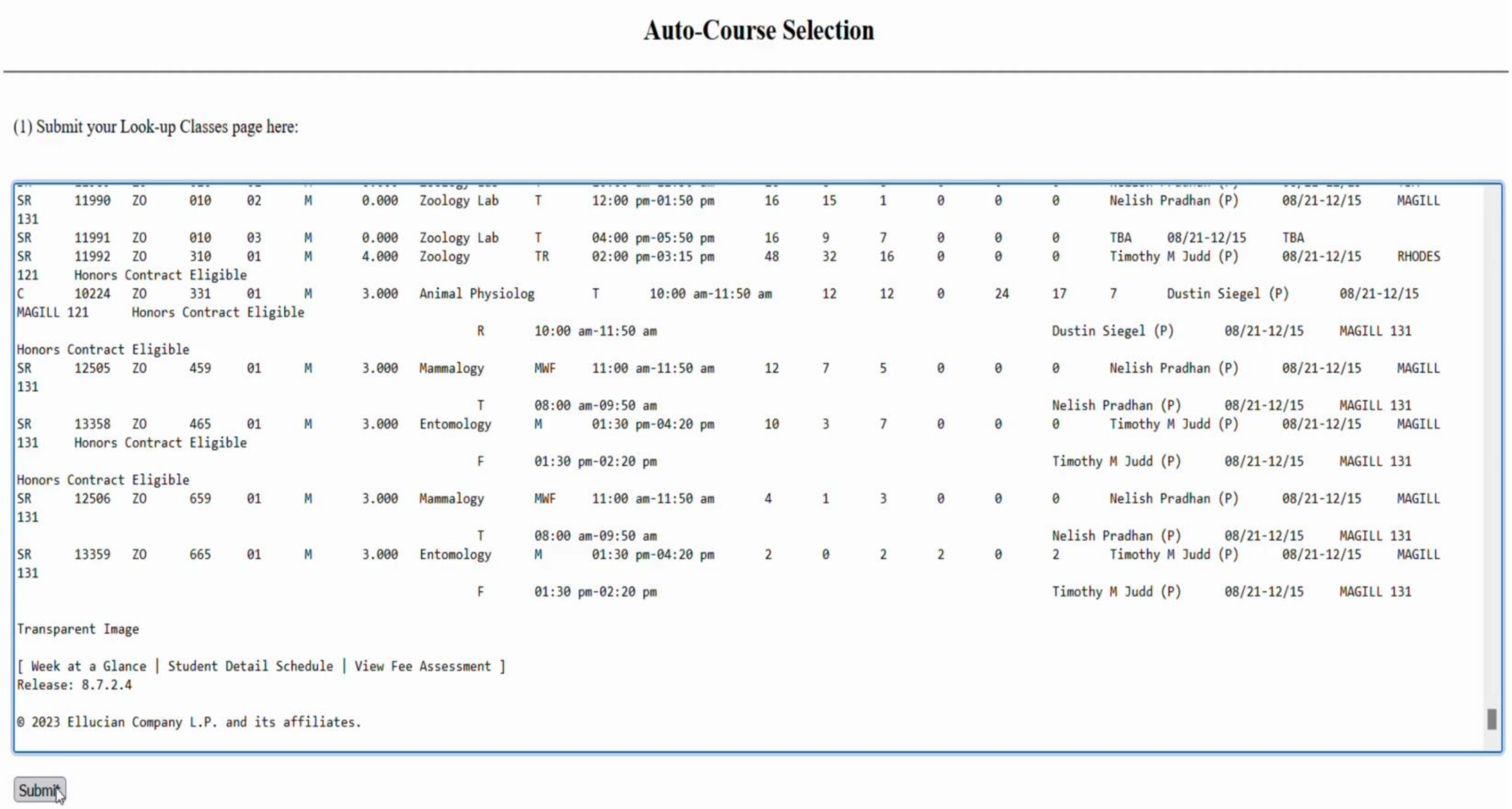
PHP call to fetch the page from the server

```
// Example fetch for bulletin data (php+js)
var bulletin_data = <?php echo json_encode(file_get_contents('https://semo.edu/student-support/academic-support/registrar/bulletin/courses/bltn_data.php'), JSON_HEX_TAG); ?>; //json_encode for escaping special characters

// If the tool is being deployed to semo.edu
// Replace the above line with the following code (js)
const url = "https://semo.edu/student-support/academic-support/registrar/bulletin/courses/bltn_data.php";
var bulletin_data = "";
fetch(url).then(function (response) { return response.text(); })
            .then(function (html) { bulletin_data = html;});
```

APPENDIX E

Web-based Auto Course Selection System Interface



APPENDIX F

Automatically Generated Email Content by the Web-based Auto Course Selection System

Auto-Course Selection

Refresh

Hi ,

I am writing to you as your primary advisor with the aim of assisting you in selecting your courses for the upcoming semester, which is set to start next week.

Based on your study progress so far, I have carefully reviewed your completed and applied courses, which include:
MA115 FE200 SO102 US107 EN100 EN140 SC155 AO120 AO125 FN235 MA223 DA100 MU190 EL274 UI100 PY222 CS351 CS440 CS480 MA464 CS101 CS155 CS245 CS265 CS288 CY201 IS245 BA252

After careful consideration, I would like to suggest the following courses for your next semester:

CS380
CS445 : Senior Standing or Status
CY310
CY320
CY440

Please also select the elective, minor, and Gen-Ed courses to meet the full-enrollment requirement!

Please note that these courses have been chosen to help you achieve your academic goals and build a strong foundation for your future studies and career. I believe that these courses will provide you with the necessary skills and knowledge to excel in your academic pursuits.

Let me know if you agree with this suggestion, then I will forward the pin to you.

George [illegible]
Southeast Missouri State University

APPENDIX G

An Example of the Generated Email

```
Student 63: ────────────────────────────────────────────────────────────────
m[redacted]s@semo.edu
S02[redacted]

Hi Matt,

I am writing to you as your primary advisor with the aim of assisting you in selecting your courses for
the upcoming semester, which is set to start on 11/06. Based on the number of completed (rather than app
lied) credit hours, you can find your priority registration date here: https://semo.edu/student-support/
academic-support/registrar/priority-registration-dates.html

I have carefully reviewed your completed and applied courses, which include:
{'CS101': 'A', 'CS155': 'A', 'CS245': 'A', 'CS265': 'A', 'CS288': 'A', 'CS351': 'B', 'CS380': 'A', 'CS44
0': 'A', 'CS445': 'IP', 'CS480': 'IP', 'CY201': 'A', 'CY310': 'IP', 'CY320': 'IP', 'CY440': 'IP', 'IS245
': 'B', 'IS299': 'A', 'MA223': 'B', 'MA464': 'C', 'BA252': 'B', 'SI001': 'IP'}

After careful consideration, I would like to suggest the following courses for your next semester:
['CS499', 'CS533', 'CY410', 'CY420', 'CY450']

Please note that these courses have been chosen to help you achieve your academic goals and build a stro
ng foundation for your future studies and career. I believe that these courses will provide you with the
 necessary skills and knowledge to excel in your academic pursuits.

Please remember to apply for graduation!

Simply reply to this email if you agree with this suggestion, then I will forward the pin to you.

If you think more discussion will be needed, feel free to reserve a timeslot form my office hours by the
 following link:
https://semo.starfishsolutions.com/starfish-ops/dl/instructor/serviceCatalog.html?bookmark=connection/54
509/schedule

Regards,
George

Total 63 studetns!
```

Future Workforce Evolution - Impact of Artificial Intelligence Across Industries

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Abstract

This study explores the impact of Artificial Intelligence (AI) on workforce dynamics, analyzing job roles, skills, and employment across eight companies of varying sizes, from small to very large, and across different industries. It highlights AI's potential to create opportunities and enhance work experiences, emphasizing the importance of human-centric skills and lifelong learning. The proposed framework offers a comprehensive perspective on AI's impact on workforce development, organized into five interconnected factors: regulatory and ethical considerations, organizational dynamics, job characteristics, skills and education requirements, and business ecosystems. It highlights the various ways AI influences the workforce. Concluding with actionable recommendations for policymakers, educators, and employers, the research underscores the necessity of strategic AI integration in enhancing innovation and AI literacy in organizations across industries.

Keywords: Artificial Intelligence, Workforce Dynamics, Human-centric Skills, Regulatory Adaptation, Business Ecosystems, Workforce Innovation, Technology Adoption

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Future Workforce Evolution - Impact of Artificial Intelligence Across Industries

Asish Satpathy and Jayaram Balachander

1. INTRODUCTION

AI has made considerable progress in the last decade and a half (Haenlein et al., 2019). The integration of AI, including narrow AI and Gen-AI, is anticipated to be a transformative force across industries, potentially contributing an estimated $13 trillion to the global economy by 2030, according to the McKinsey Global Institute (Bughin J. et al., 2018). Early AI adoption is highlighted as a key driver for substantial economic benefits, with front-runners achieving a 122% cumulative cash flow increase compared to a -23% loss for laggards. These benefits arise from front-runners' ability to leverage economy-wide output gains and competitive advantages, while laggards experience slower returns and increased losses to peers, highlighting the urgency of timely AI adoption. With the rise of generative AI in recent years, AI has gone mainstream, transforming industries, reshaping economies, and even redefining the nature of work itself (Brynjolfsson et al., 2017; Howcroft, D., & Taylor, P., 2023). By automating tasks, creating new jobs, and altering workflows, AI introduces a complex interplay of opportunities and challenges for the workforce (Frank et al., 2019; Tschang & Almirall, 2021), highlighting the multifaceted implications of this transformative technology.

One perspective is that AI can increase efficiency and productivity, freeing workers to focus on more creative and strategic tasks. It can also help improve decision-making and predictive analytics, providing businesses valuable insights into their operations. Additionally, AI can create new jobs in data science, machine learning, and generative AI (Davenport et al., 2018; Brynjolfsson E. et al., 2023).

Contrary to the first perspective, others feel that AI also has the potential to displace some or a lot of workers, especially those jobs that are repetitive or can be automated. It could also lead to increased inequality, as those with the skills to work with AI are likely to benefit more than those who do not have the skills (Acemoglu et al., 2018).

Understanding the impact of AI on the workforce is paramount in navigating the rapidly evolving landscape of industries in which technology plays a key role (El-Farr, H. (Ed.)., 2024). As AI permeates diverse sectors, comprehending its effects on employment, job roles, and skill requirements becomes critical (Autor D. H., 2015; Shiohira, K., 2021). This understanding is crucial because AI is automating routine tasks and shaping the nature of work itself, displacing certain job types, particularly those involving repetitive tasks, and necessitating the acquisition of new skills for the workforce. Studying this impact provides insights into the transformational shifts occurring within organizations, shedding light on the potential displacement of certain job types, the emergence of new roles, and the necessity for upskilling and adaptation (Manyika et al.; 2017, Morandini, S., 2023). Furthermore, this exploration aids in formulating proactive strategies for policymakers, educators, employers, and individuals, enabling them to leverage AI's potential while mitigating associated risks, such as bias in algorithms and data privacy concerns, fostering trust, and ensuring a smooth transition to an AI-integrated workforce.

This research aims to assess the impact of AI on employment and workforce development by exploring how these technologies are changing the nature of work and the skills required to succeed in the job market. The work draws on existing studies, specifically in generative AI and its impact on jobs and productivity (Eloundou et al., 2023; Sachs,2023). The research employs quantitative and qualitative methods to gather insights from diverse industries, including education, retail, healthcare, and finance (Audet et al., 2001; Myers, M. D. (2019). Qualitative methods like interviews and case studies provide an in-depth understanding of individual and organizational experiences with AI integration. The study aims to capture a holistic view of AI's impact by focusing on diverse industries. In future related work, quantitative methods such as surveys and sentiment analysis will be employed to measure AI's impact on job displacement, job creation, and changes in skill requirements, with findings contributing to empirical validation of the proposed strategic frameworks for workforce adaptation to guide policymakers, educators, and business leaders in preparing for and leveraging AI advancements.

This research also offers valuable insights for Information Systems (IS) educators that can directly inform curriculum development and teaching strategies. Understanding the evolving skill sets required in an AI-driven job market enables educators to tailor their programs to better prepare students for future careers. The findings from this study can help IS educators incorporate relevant AI technologies and concepts into their courses, ensuring that students gain practical, up-to-date knowledge that aligns with industry demands. Additionally, exploring case studies and real-world applications of AI in various sectors can provide rich, contextual examples to enhance classroom learning and discussions.

This paper begins with a literature review and research methodology overview, employing qualitative methods and multiple case studies to explore AI's impacts. It details data collection, participant selection, and analysis techniques. The article synthesizes expert interview insights on themes like job transformation, skill evolution, and transition strategies, proposing an augmented framework integrating established models. It emphasizes regulatory, organizational, and educational considerations in AI adoption, discussing associated challenges and opportunities. The conclusion offers recommendations for policymakers, educators, and employers, advocating proactive adoption strategies and ethical governance in the evolving AI-driven job market.

2. LITERATURE REVIEW

The impact of AI on the workforce has been a focal point of scholarly discussion and research over the past decade. As AI technologies have advanced, their influence on employment, job roles, and skill requirements has become increasingly significant, prompting extensive academic inquiry. Studies such as those by Brynjolfsson and McAfee (2018) have highlighted how AI and automation can drive job displacement and creation, reshaping the labor market. Frey and Osborne (2017) quantified the susceptibility of various job categories to automation, emphasizing the transformative potential of AI. The World Economic Forum's Future of Jobs Report (Di Battista et al., 2023, May) further underscores this dynamic, noting that technological adoption, particularly in AI, big data, and cloud computing, will remain key drivers of business transformation, with significant implications for job growth and displacement. The report also highlights the global divergent outcomes in labor markets, driven by economic, health, and geopolitical trends. It emphasizes the need for continuous adaptation in skills and training to meet the demands of an AI-driven economy. These comprehensive investigations underscore the critical need to understand AI's multifaceted impact on the workforce, paving the way for informed policymaking, educational reforms, and strategic business planning to utilize AI's potential while mitigating its risks.

AI and Job Displacement

A substantial body of literature addresses the potential for AI to displace jobs, particularly those involving routine and repetitive tasks. Acemoglu and Restrepo (2018) analyzed the impact of automation on employment and found that automation significantly reduces employment in routine job categories. Chui, Manyika, and Miremadi (2016) indicated that about 60 percent of all occupations could see 30 percent or more of their constituent activities automated. Some studies estimate that up to half of all job tasks in the US could be automated with current AI-enabled technologies (Tyson et al., 2022; Manyika et al., 2017).

The long-term socioeconomic impacts of job displacement are significant and vary across industries. In manufacturing, for example, AI-driven automation can lead to substantial job losses as machines replace tasks traditionally performed by workers. Conversely, sectors such as technology and healthcare may experience different impacts. In tech, AI can create new job opportunities in areas like AI development and data analysis, while in healthcare, automation might enhance productivity and reduce costs, potentially creating new roles in tech support and management. These varying impacts highlight the need for sector-specific strategies to address the broader socioeconomic consequences of job displacement.

The contrast with job creation is notable. While AI can displace existing roles, it generates new employment opportunities and drives economic growth. For instance, AI advancements have led to new industries and job categories that did not exist before. This shift underscores the importance of adapting skills policies and regulations to address inequality and ensure the benefits of AI are widely distributed. Proactive measures, such as profit sharing, digital capital taxation, and reduced working hours, are essential to mitigate the risks of increased inequality and help workers transition into new roles within an evolving job market (Ernst et al., 2019).

Job Creation and Transformation

Conversely, AI is recognized for its potential to create new job roles and transform existing ones. Recent research highlights that while AI and automation may eliminate specific jobs, they also generate new opportunities in data science, machine learning, and AI ethics. Agrawal, Gans, and Goldfarb (2019) discuss how AI's role in enhancing prediction capabilities leads to the creation new tasks and job categories. This new technological age, marked by rapid advancements in machine learning and autonomous decision-making, is engendering significant opportunities for innovation across various industries, including finance, healthcare, manufacturing, retail, supply chain, logistics, and utilities (Dwivedi et al., 2021). The World Economic Forum's Future of Jobs Report (Di Battista et al., 2023) supports this view, predicting a net positive effect on employment, with significant job creation in technology-driven industries, particularly AI and digital transformation. This report also emphasizes the necessity for upskilling and reskilling initiatives to equip the workforce with the skills required for these emerging roles, ensuring that the benefits of AI-driven job creation are widely distributed.

Evolving Skill Requirements Due to AI Integration

The literature emphasizes the evolving skill requirements due to AI integration in the workplace. Recent studies highlight the growing demand for advanced technological skills, critical thinking, and adaptability. For instance, Bughin et al. (2018) identify the increasing necessity for workers to develop proficiency in AI-related technologies and analytical capabilities. A study by Deloitte (Insights., 2020) underscores the importance of continuous learning and upskilling to ensure workers can transition into new roles created by AI advancements. This necessitates a shift in educational paradigms, emphasizing interdisciplinary learning and developing technical and soft skills. Furthermore, the World Economic Forum (Di Battista et al., 2023) emphasizes that the most in-demand skills include complex problem-solving, critical thinking, creativity, technological literacy, and socio-emotional skills, highlighting the need for a holistic approach to workforce development.

Organizational and Ethical Implications

Studies also explore the broader organizational and ethical implications of AI adoption. Recent research by Ransbotham et al. (2020) highlights how AI reshapes organizational structures, necessitating new management strategies and focusing on human-AI collaboration. This involves rethinking traditional workflows and fostering a culture of continuous learning to integrate AI technologies effectively. The ethical considerations of AI deployment, such as bias in algorithms and data privacy concerns, have been extensively examined by scholars like Fjeld et al. (2020), who advocate for robust ethical frameworks to guide AI implementation. These frameworks emphasize the importance of transparency, accountability, and fairness in AI systems to ensure they are developed and used responsibly.

Policy and Education Recommendations

Recent research suggests that policymakers should focus on mitigating the adverse effects of AI through social safety nets and job transition programs (Oluwaseyi et al.,2024). Additionally, George (2023) emphasizes the role of education in preparing the future workforce, advocating for curricula that incorporate AI literacy and foster adaptability. This includes integrating interdisciplinary learning approaches and developing technical and soft skills to ensure individuals can navigate the evolving job market. The World Economic Forum (Di Battista et al., 2023) further highlights the importance of continuous learning and upskilling initiatives to maintain a competitive and resilient workforce in rapid technological advancements.

Significance of This Work

This research contributes significantly to understanding AI's impact on the workforce by addressing several critical gaps in the existing literature. While prior studies have predominantly focused on the displacement and creation of jobs due to AI, this work provides a qualitative analysis of the transformational shifts in job roles and skill requirements across diverse industries. By employing a multiple case study approach, this research offers a detailed examination of the effects of AI in real-world business contexts, which is less explored in current literature. Moreover, this study utilizes in-depth qualitative data from industry experts. It provides a comprehensive view by combining insights from various sectors and professional backgrounds, all weighing in on their AI strategies. This approach allows a richer understanding of how AI technologies reshape organizational structures, job functions, and skill needs.

One of the highlights of this paper is the development of an augmented framework for understanding AI's impact on the workforce. The proposed framework, detailed in the section "Comprehensive Framework for Understanding AI's Impact on Workforce Transformation," combines established IS models and focuses on regulatory, organizational, and educational aspects. It provides a thorough perspective on how AI influences job roles and skill requirements. By providing a structured approach to analyzing the multifaceted effects of AI, this framework, upon empirical validation, will make a significant contribution to the literature, bridging the gap between theoretical explorations and practical strategies for workforce development in the AI-driven economy.

3. METHODOLOGY

This research focuses on the "how" and "why" aspects of the impact of AI on the workforce. Qualitative research has traditionally been chosen when the primary research objective is to improve understanding of a phenomenon, especially when it is complex and deeply embedded in its context.

We selected a multiple case study design to thoroughly examine AI's impact on different business environments. Case studies are effective for gaining insights into business issues, management decisions, or emerging theories (Ghauri, 2004). This approach enabled us to explore diverse contexts and compare findings across organizations (Baxter et al., 2008; Yin, 2009). By analyzing eight distinct cases, we developed a framework to explain AI's effects on the workforce through the comparative analysis of responses from these cases. By selecting a diverse array of industries and company sizes, the study aimed to shed light on how AI reshapes roles and responsibilities in businesses of all sizes.

The research aims to understand how both Narrow and Generative AI is redefining work from small businesses to large corporations. The methodology was designed to ensure comprehensive data collection, capturing various perspectives on AI's impact, robust analysis using advanced techniques like topic mining, adherence to ethical standards, and selecting a representative sample of companies to provide a well-rounded view of workforce dynamics in the age of AI.

Data Collection Method

In each case study, data was collected through semi-structured interviews. This interview format was chosen to facilitate a deep and comprehensive exploration of participants' individual experiences and their perspectives on AI in the workplace. Semi-structured interviews allowed for flexibility in questioning, enabling interviewers to probe deeper into specific areas of interest that emerged during the discussions. Data were primarily collected firsthand from participants to ensure the relevance and accuracy of the findings. This approach provided current and contextually rich information, ensuring that the data reflected the most recent developments and trends in AI adoption within organizations, while also capturing authentic insights into how AI reshapes job roles, responsibilities, and organizational dynamics through a focus on firsthand accounts.

Participant Selection Criteria

While specific details are restricted due to mutual agreements with participating organizations, we provide a general overview of our selection criteria and procedures to ensure the study's validity. These criteria included industry representation (such as finance, education, public sector, utilities, and high tech), company size (ranging from small businesses with 20+ employees to large corporations with 20000+ employees), and varying levels of technology adoption and AI integration.

Eight companies were selected based on these criteria, ensuring a comprehensive view of AI's impact across industries. These companies represented a cross-section of the market, providing insights into diverse AI applications and their implications for the workforce. Interviewees were key decision-makers and practitioners with substantial experience in business and technology, specifically AI technologies and their implementation. The participants have been active in their respective industries for over two decades. This selection approach provided a comprehensive and well-rounded perspective on AI's impact across different sectors.

Ethical Considerations

The ethical considerations included ensuring the confidentiality of the participants and their organizations, obtaining informed consent from all participants, and secure handling of sensitive data. The research adhered to the ethical guidelines of the institution and any relevant legal requirements regarding data protection and privacy.

Limitations and Delimitations

We acknowledge limitations such as the potential for bias in qualitative research, the limited number of case studies, and the specific focus on certain industries, which may not be generalizable to all sectors. Delimitations might include the limited geographical scope of regions and the focus on sizes and types of companies.

Analysis Techniques

The interview data analysis utilized a combination of AI and human expertise. Large Language Models (LLM) (Chang et al., 2023), including ChatGPT 3.5 and Gemini, were employed to transcribe and process the interview recordings. The audio data was first transcribed into text, enabling the LLM to apply advanced algorithms and natural language processing techniques to identify recurring themes and patterns within the data (Peña et al., 2023). This AI-driven process efficiently highlighted key topics and revealed interconnections between various subjects. However, the role of human researchers remained indispensable in this process. The researchers carefully interpreted the AI-generated results, synthesizing qualitative insights from the interviews and ensuring that the final analysis was coherent, contextually relevant, and aligned with the study’s goals. This approach enhanced the accuracy and depth of our findings, making the use of AI a valuable complement to the human-led analysis.

Timeline

The research follows a structured timeline, beginning with a preliminary literature review and design phase. This initial phase involved comprehensively examining existing literature and developing a robust research design. The study was conducted over six months, from June 2023 to Dec 2023. This period included the phases of interview scheduling and data collection. Each interview session lasted approximately 45 to 60 minutes without additional follow-up discussion. During data collection, audio recordings were made and transcribed for further analysis. The subsequent phase focused on a thorough data analysis using the LLMs, which facilitated the extraction of meaningful insights and patterns from the collected data. The final phase involved synthesizing the findings, leading to the conclusions and results reported in the article.

4. SYNTHESIS OF QUALITATIVE INSIGHTS FROM EXPERT INTERVIEWS

The interviews aimed to capture executives' perspectives on various AI-related issues, including how AI might transform job landscapes, affect job types, and create new roles. We examined several key topics, such as the vulnerability of specific jobs to AI-induced displacement, the continuing need for human expertise, and how AI integration is reshaping required skills. Discussions also addressed strategies for managing AI-driven workforce transitions, the effects of different AI technologies on employment, and potential changes to the traditional workweek model. The discussions were structured into the following major themes:

Workforce Satisfaction and AI Impact:

- Level of contentment with the current workforce structure.
- Predictions on how AI will influence the current workforce.

Job Landscape Transformation:

- Types of jobs expected to be affected by AI.
- The time frame for these changes.
- New roles that AI is anticipated to create.

Vulnerability and Indispensability:

- Jobs and industries at risk of AI-induced displacement.
- Roles where human expertise is considered irreplaceable.

Skill Evolution:

- Changes in the skills and qualifications demanded by AI adoption.
- Specific examples of new skill requirements.

Transition Strategies:

- Plans for managing the transition of employees affected by AI.
- Details of initiatives and strategies in place or proposed.

AI Technologies and Their Influence:

- Disruptive potential of various AI technologies (Generative AI, Predictive AI, etc.).
- Examples of their influence on the workforce.

Workweek Paradigm Shift:

- Perspectives on the future of work schedules and structures.

- Expectations for skill shift away from the traditional model.

Policy and Education Recommendations:

- Advice for policymakers, educators, and employers.
- Strategies to navigate and address the impact of AI on employment.

Each theme was supported by qualitative insights (e.g., expert opinions or anecdotal evidence) gathered from the responses. For instance, expert opinions highlighted specific job roles at risk of automation, such as data entry positions, while identifying areas where human expertise remains crucial, like in creative and ethical decision-making roles. This organization allowed for a comprehensive understanding of the multifaceted effects of AI on the workforce, revealing both the vulnerabilities and opportunities AI presents across various industries.

5. INSIGHTS FROM QUALITATIVE RESEARCH

The research findings underscore the significant impact of AI on the workforce and the urgent need for organizations to adapt. Key themes include the transformation of work dynamics, the evolution of skills, and challenges such as talent acquisition optimization and rapid technological change. While AI is seen as creating new job roles, there are concerns about vulnerable job types and the need for a blend of technical and soft skills. Strategies for a smooth transition include addressing legal, educational, and leadership aspects emphasizing continuous learning. Additionally, ethical considerations and regulatory frameworks are crucial in managing this AI-driven transformation, highlighting the need for transparent and proactive leadership. Overall, the sentiment regarding the findings leans towards a positive outlook, acknowledging AI's potential to create new opportunities, enhance efficiency, and improve work experiences. There is an emphasis on a human-centric approach, highlighting collaboration and augmentation rather than replacement by AI. Crucial human skills such as creativity, critical thinking, and ethical judgment are essential to future work dynamics.

Table 1 (Appendix) presents a structured summary of the research themes and key findings from the qualitative research on AI's impact on the workforce. While much of the findings align with existing research, our study introduces a nuanced understanding of how these trends manifest differently across industries and company sizes, offering a sector-specific perspective on AI's impact. Moreover, the framework developed in this study provides actionable insights for integrating AI into workforce strategies, which may not be as explicitly detailed in the existing literature.

The sentiments of each executive across all the evaluated questions are concisely captured in Table 2. The table presents an overview of AI's impact across various industries, workforce satisfaction, job types affected, potential job creation by AI, vulnerable roles, necessary new skills, and areas of focus. In finance, hiring challenges exist, and AI significantly impacts customer service agents, emphasizing the need for operationalizing AI and education. Education sector employees are delighted, viewing AI as transformative, with a focus on machine learning and adaptive learning improving the way an individual learns. Another finance segment cites mixed satisfaction due to the pandemic, with repetitive tasks being vulnerable and a focus on transparency. High Tech has an optimistic outlook on AI, affecting quality control and finance jobs, and emphasizes data tagging skills. The executives from the above sectors agree that customer service roles will be significantly impacted. The government sector is unprepared for AI, which impacts clerical employment and focuses on adaptability. Utilities face a labor shortage and see AI as a solution, particularly in routine water treatment tasks, with a focus on Supervisory Control and Data Acquisition (SCADA) and ethics. Healthcare/Education, unspecified in workforce satisfaction, views AI's impact as subtle, affecting educators and tutors, with ethical concerns as a focus. Lastly, highly satisfied with AI's moderate effect on developers, the software industry stresses the importance of predictive analysis and productivity.

The findings summarized in Table 1 align with existing studies on AI's impact on the workforce. For instance, recognizing the need for adaptation and transformation in response to AI-driven changes supports the broader literature that emphasizes organizational agility in the face of technological advances (Wamba, S. F., 2022). The expectation of significant changes in work, coupled with a strong focus on continuous learning, aligns with previous studies emphasizing the critical need for skill adaptation and lifelong learning (Gharahighehi A. et al., 2024). The concerns about rapid technological change and the challenges in talent acquisition and placement reflect established research on effective strategies to manage workforce transitions (Pradhan, I. P., & Saxena, P., 2023). Additionally, the observation that AI displaces certain job types and creates new roles is consistent with existing literature on the dual impact of AI on employment dynamics Olaniyi, O. O. et al., 2024).

6. COMPREHENSIVE FRAMEWORK FOR UNDERSTANDING AI'S IMPACT ON WORKFORCE TRANSFORMATION

The pervasive influence of AI on the workforce presents a complex blend of effects that differ widely across different industries, necessitating a robust framework to comprehend this impact fully. We propose an augmented framework that captures our findings from the qualitative study and integrates elements from diverse established IS models and theories, including the business ecosystem (Moore, 1993), workforce skills tailored for Industry 4.0 (Ada et al., 2021), and technology and innovation adoption theories (Koul et al., 2017), such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Theory of Planned Behavior (TPB) (Ajzen, 1991) and theory of diffusion (Rogers, 2014). This framework captures our qualitative study findings and offers a structured approach for future empirical validation. While this paper focuses on delineating the framework's components and their interconnections, it sets the stage for future research to assess its practical applicability. Our work provides a conceptual foundation that academics and practitioners can further refine and adapt for real-world applications. Additionally, empirical validation of the proposed framework in specific industries such as healthcare, finance, government, and others can offer deeper insights, thereby advancing the existing body of knowledge in this critical area.

This framework (Figure 1) provides an integrated view of how AI impacts workforce development. It is divided into five interconnected sections, illustrating the various factors influencing this impact.

Regulatory and Ethical Factors
This part of the framework focuses on the role of legal regulations, the careful management of high-risk AI applications, and the ethical deployment of AI technologies, emphasizing transparency, fairness, safety, clarity, privacy, and security. It highlights how AI governance is a critical factor significantly influencing the workforce. Additionally, it's essential to recognize that the way managers think and make decisions and who has the final say or control in AI matters are vital in ensuring AI is used responsibly in the workplace.

Organizational Dynamics
This framework element examines how organizations navigate integrating and adopting AI technologies. This includes considering the role of leadership, how quickly AI is adopted, how effectively human workers and AI systems can work together, and the specific requirements of different industries. It is about the factors inside a company that can help AI become a part of the workplace or block its progress. Notably, the type of technology used, how a company operates, how managers think and make decisions, whether there are enough employees who understand technology, the company's size, and how much money it has all play crucial roles in how an organization adapts to AI.

Job Characteristics
This section highlights the job roles most impacted by AI, particularly those that are routine, involve transactions or require content creation. It indicates that the effect of AI will differ across job categories and depend on the presence of staff with the proper knowledge, leading to changes in the workforce structure.

Skills & Education
This section recognizes the growing need for tech education, AI understanding, and digital skills to collaborate with AI systems. It suggests that as AI use grows, the skills that workers need will change. The 'Existing set of skills' and 'Level of AI literacy' directly connect to how many tech-savvy employees are available.

Business Ecosystems
This demonstrates that the impact of AI extends beyond altering companies' internal work processes. It affects a range of external business elements, such as how companies outdo each other, make their operations more efficient, how consumers decide to act, what skills are in demand, changes in regulations, where the money and support for AI projects come from, and how firms work together. It also looks at AI's broader effects on ethics and society. Within the industry, factors like a drive to stay ahead and partnerships are part of 'Competitive Advantage' and 'Collaborations & Partnerships', driving change and new ideas in the field.

The central octagon, "Impact of AI on Workforce Development," is the focal point where all these factors converge, suggesting that AI's impact on the workforce is influenced by regulatory, ethical, organizational, and educational aspects.

Our augmented framework enriches the traditional technology adoption models, such as TAM and TPB, by considering the specific behaviors and intentions that drive AI adoption and usage within the workforce. For instance, TAM focuses on perceived usefulness and ease of use as primary motivators for technology adoption. In the context of AI, this might involve an organization assessing whether AI tools will enhance job performance (usefulness) and whether employees believe they can use AI without undue effort (ease of use). An example could be a financial institution implementing AI for customer service. The TAM would lead us to question whether AI chatbots are more efficient than human employees in handling customer queries and whether employees feel confident managing and overseeing these chatbots.

The TPB adds another layer, considering the role of social pressure and the control individuals feel over their actions. So, if an organization's culture highly values innovation, employees might feel a social obligation to embrace AI. However, they must also feel they have the necessary resources and support to use AI effectively. For example, a manufacturing company may introduce AI-driven predictive maintenance on its machines. TPB would suggest examining if workers feel that using AI is expected and supported in their company culture and if they have the training and time to incorporate AI maintenance tools into their workflow.

The diffusion of innovation theory helps explain how, why, and at what rate new ideas and technologies spread. This theory suggests that the adoption of new technologies like AI is influenced by factors such as the technology's relative advantage, compatibility, complexity, trialability, and observability. For example, organizations are more likely to adopt AI if they perceive it as superior to existing methods (relative advantage), compatible with their current systems and practices (compatibility), easy to understand and use (complexity), and if they can experiment with the technology before full implementation (trialability). Observing successful AI implementations in similar organizations (observability) also encourages adoption.

The proposed framework broadens the scope of existing models by integrating organizational dynamics, such as a company’s readiness to adopt AI, and job characteristics that identify which roles are most susceptible to automation. Additionally, it emphasizes the evolving skill sets and educational needs required to work effectively with AI while considering the ethical and regulatory frameworks that influence how these technologies are implemented.

In practical terms, this framework is a comprehensive guide for organizations to manage AI integration. It aids in designing tailored training programs, change management initiatives, and policy development strategies that align with both individual employee readiness and overarching business goals. The unique contribution of this framework lies in its multi-dimensional approach, which moves beyond merely addressing technology adoption. It combines technical aspects of AI with essential considerations around regulation, ethics, and education. This comprehensive perspective makes the framework flexible and applicable across various industries and organizational contexts, providing a more holistic view of AI’s impact on workforce development. One key insight from our framework is the central role that continuous learning and skills evolution play in mitigating the potential negative impacts of AI on the workforce. Additionally, we emphasize the importance of leadership and organizational culture in fostering an environment receptive to AI adoption, ensuring that AI is integrated ethically and effectively.

7. RECOMMENDATIONS

In the wake of our findings on the impact of AI on the workforce, we present a set of targeted recommendations aimed at guiding policymakers, educators, and employers. These recommendations are designed to optimize the integration of AI within various sectors, ensuring that the transition towards more AI-inclusive operations maximizes benefits while minimizing potential disruptions. For policymakers, the focus is on crafting supportive regulations and fostering public-private partnerships. Educators are encouraged to embed AI literacy into their curricula and focus on critical, adaptable skills. Employers are advised to maintain a positive outlook on AI adoption, invest in their workforce's development, and nurture a learning culture. These guidelines act as a compass for stakeholders, helping them navigate the complex landscape of AI in the workforce and promoting a collaborative and proactive approach to this technological evolution.

For Policymakers

Craft AI-Supportive Regulations:
Policymakers should create laws encouraging AI innovation while upholding ethical standards. This involves balancing promoting technological advances and protecting individual rights and societal values.

Strengthen Public-Private Partnerships:
Encourage collaborations between government entities and private companies to maximize the benefits of AI. Such partnerships can accelerate AI development and application, sharing expertise and resources effectively.

Anticipate and Address Workforce Impacts:
Foreseeing and mitigating AI's adverse effects on employment is crucial. Policies could include support for job transition programs, unemployment benefits for displaced workers, and initiatives to close the skills gap.

For Educators

Embed AI Literacy in Learning:
Update educational programs to include AI knowledge, ensuring students understand not just the technology but also the ethical implications of its use.

Enhance Critical Skills:
Educators should emphasize skills AI cannot easily replicate, such as problem-solving, critical thinking, and creativity, to prepare students for a rapidly changing job market.

Integrate Tech in Teaching:
Adopt and integrate digital tools in teaching methods to ensure students are comfortable with technology and can work seamlessly with AI systems in their future careers.

IS educators, in particular, must update their curricula to integrate comprehensive AI literacy, emphasizing both the technical dimensions and ethical considerations of AI usage. As AI literacy becomes a critical component of education, it is essential that students not only grasp the technical underpinnings but also understand the societal and ethical implications, such as AI bias and its influence on employment outcomes (Salhab, R., 2024).

Given that AI cannot easily replicate advanced skills such as problem-solving, critical thinking, and creativity, educators should focus on fostering these capabilities in students to prepare them for a rapidly evolving job market (World Economic Forum, 2024). Incorporating AI-driven tools and digital platforms into the teaching process provides students with practical, hands-on experience, making them more proficient with these emerging technologies. Educators must participate in continuous professional development to stay abreast of AI advancements and effectively integrate these insights into their teaching. Ethical instruction is crucial to address AI biases and promote the development of transparent and equitable AI systems (Han, B. et al., 2023, June).

For Employers

Adopt AI with Openness:
Companies should approach AI integration optimistically, recognizing the technology's potential to enhance productivity and innovation.

Invest in Employee Development:
Allocate resources to train and develop employees' skills continuously, ensuring they remain competitive as AI evolves workplace demands.

Foster a Learning Environment:
Establish a company culture that promotes ongoing education, adaptability, and collaboration, which is essential for maximizing AI's advantages in the workplace.

8. CHALLENGES & OPPORTUNITIES

Researching AI's impact on the workforce presents several significant challenges. Data availability and quality remain a primary concern, as obtaining accurate and comprehensive data across various industries and regions can be hindered by privacy concerns, inconsistent data collection practices, and proprietary restrictions. Additionally, the rapid pace of technological change makes it challenging to keep research current, requiring continuous updates and adjustments to maintain relevance and accuracy. Ethical considerations, such as bias in algorithms and data privacy, further complicate the research landscape, necessitating careful navigation to ensure fairness, transparency, and accountability. Finally, predicting the long-term impacts of AI on job markets and employment trends involves a degree of uncertainty and speculation influenced by economic conditions, policy changes, and technological breakthroughs.

Despite these challenges, there are substantial opportunities for our research on AI's impact on the workforce. This research can lead to innovative solutions for workforce development

by identifying evolving skill requirements and informing targeted training programs and curricula. Additionally, it can uncover ways to enhance human-AI collaboration, improving job satisfaction and performance by integrating AI technologies with human roles effectively. The findings can also inform the creation of policies and regulations that address AI's ethical and social implications, ensuring responsible and equitable deployment of these technologies. Furthermore, by highlighting specific areas with significant skills gaps, the research can drive more focused and effective upskilling and reskilling initiatives, helping workers transition into new roles created by AI. Ultimately, leveraging the opportunities presented by AI can drive economic growth and innovation, providing insights into how different sectors can adopt AI technologies to enhance productivity, create new job roles, and boost overall financial performance.
Researchers can collect survey data from various industries and stakeholders to test the proposed framework. Surveys can be designed to capture information on multiple dimensions, such as regulatory and ethical factors, job characteristics, organizational dynamics, skills and education, and business ecosystems. Respondents should include a mix of industry leaders, policymakers, educators, and workers to ensure a comprehensive understanding of AI's impact. Questions can be tailored to assess the perceived influence of AI on job roles, skill requirements, organizational changes, and regulatory needs. Additionally, longitudinal studies can be conducted to track changes over time, providing insights into the dynamic nature of AI adoption and its effects on the workforce. Analyzing the survey data will allow researchers to validate and refine the framework, ensuring it accurately reflects the real-world impact of AI on workforce development. This empirical validation will help stakeholders design practical strategies for navigating the AI-driven transformation of the labor market.

8. CONCLUDING REMARKS

As we conclude our analysis, we must recognize the twofold nature of AI's impact on employment. Our study illuminates the fact that AI's role extends beyond mere technological advancement—it is a driving force behind the transformation of the workforce that is marked by the emergence of new roles driven by innovation and the concurrent reevaluation, or even obsolescence, of existing jobs, signaling a potential paradigm shift in the employment sector.

Decision-makers—from policy architects to corporate executives and education strategists—must rise to the occasion with a proactive stance toward adopting AI. Cultivating a culture where ongoing learning and skill enhancement are embedded in the organizational fabric is essential. Such a culture is the key to equipping the workforce with the tools required to excel in an AI-enhanced future.

This transition must be navigated with a keen ethical compass and a responsive regulatory framework. The advancement of AI technologies raises significant ethical and governance questions that demand attention to ensure their benefits are distributed fairly and justly. Standing at the brink of an era where AI is redrawing industry boundaries, our framework is a strategic instrument for leveraging AI's capacity for change thoughtfully and innovatively. We acknowledge that the proposed framework needs to be tested and validated by empirical evidence and refined through its application in varied organizational contexts.

The proposed framework integrates elements from several established models, including the TAM**,** TPB**,** the concept of business ecosystems and the diffusion of innovation theory**.** Doing so builds upon existing technology adoption theories and organizational dynamics, enriching them with insights related explicitly to AI's impact on workforce development. The framework also incorporates regulatory, ethical, and educational perspectives, creating a multi-dimensional understanding of how AI influences job roles, skills, and organizational structures. This connection to existing theories provides a solid conceptual foundation for understanding AI's role in workforce transformation, bridging the gap between theoretical explorations and practical strategies.

The impact of the framework’s components can vary significantly across industry verticals. For example, governance and ethical considerations may carry greater importance in highly regulated sectors such as healthcare or finance, while innovation may take precedence in industries like technology or entertainment. Conducting industry-specific empirical validation of the proposed framework could shed light on these variations, providing deeper insights into the unique dynamics of each sector. Such an approach would help refine the framework, ensuring it is tailored to the unique needs of each sector and promotes equitable and effective adoption of AI technologies.

We emphasize the necessity for a dynamic, multi-dimensional approach to AI's integration into the labor market. The changing landscape of industries, the evolving nature of job roles, and the rapid pace of technology call for AI strategies to be adaptable and visionary.

As the horizon of AI's influence broadens, these strategies must account for the pace of change. They must facilitate the evolution of skills, ensure the alignment of educational systems with emerging industry needs, and anticipate the creation of new value chains. Equally important is the commitment to an inclusive transition that mitigates the risks of inequality and addresses the socioeconomic impacts of automation.

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APPENDIX

Figures & Tables

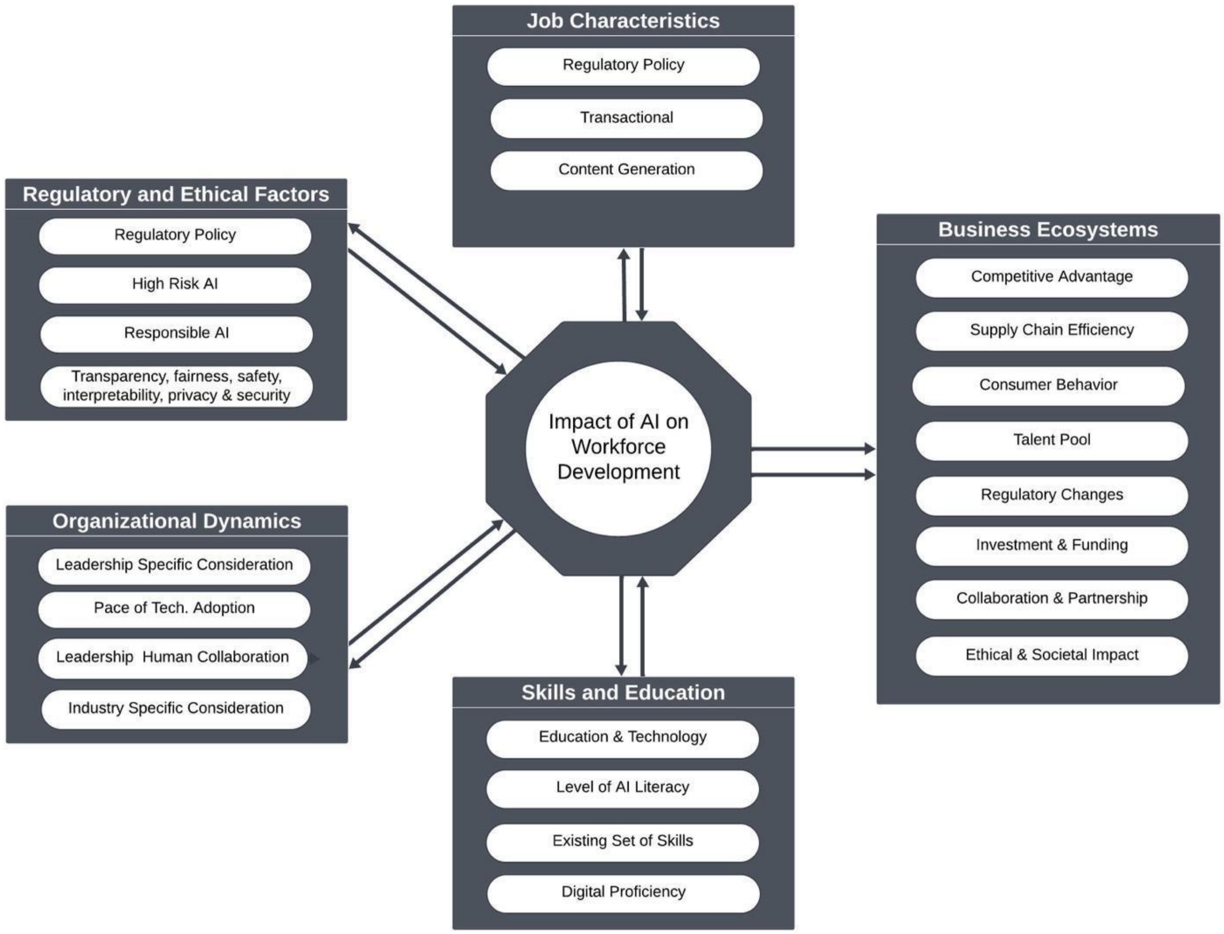

Figure 1: Integrated framework for AI impact on the workforce development

Research Themes	**Summary of Findings**
Workforce satisfaction and transformation	Organizations recognize the need to adapt and express readiness for transformation in response to AI-driven changes in the workforce (Brynjolfsson et al., 2023).
Impact of AI on workforce dynamics	AI is expected to alter the nature of work significantly, necessitating agile strategies to manage these changes (Chui et al., 2016).
Future of work and skills evolution	Continuous education, lifelong learning, and skill adaptation are expected to be in demand (Bughin et al., 2018).
Workplace location and learning	There is a focus on skill acquisition independent of the workplace location.
Talent acquisition and placement challenges	Talent acquisition and placement optimization are highlighted in the face of AI advancements.
Challenges of rapid change	Rapid technological change is a central concern, with a need for ongoing learning and adaptability.
Impact on job types	Certain job types are vulnerable to AI and automation, with an emphasis on human-AI collaboration and ethical considerations.
Creation of new jobs	AI is seen as creating new roles, leading to shifts in job quality, ethics, and specialization across industries (Agrawal, Gans, and Goldfarb (2019).
Workforce composition changes	Anticipated changes in employment types, including gig and contract work, and the development of new job roles and definitions.
Vulnerable and irreplaceable job roles	Some roles are susceptible to AI displacement, while human expertise in decision-making remains irreplaceable.
Skills and qualifications evolution	The importance of critical oversight, operational adaptability, and a blend of technical and soft skills is emphasized.
Strategies for a smooth transition	Strategies for a smooth transition include legal, educational, leadership considerations, and continuous learning.
Influential AI domains	Generative AI's influence on work dynamics, education, and business models is a recurring theme.
Industry impact	Unique industry transformations are expected, necessitating specialized upskilling and adaptation strategies.
Ethical considerations	Building trust, ensuring fairness, and addressing AI system biases are vital concerns (Fjeld et al., 2020).
Regulatory landscape	Evolving regulations are needed to balance innovation with risk mitigation and address legal and ethical challenges (Fjeld et al., 2020).

Education and training	Curriculum adaptation and reskilling initiatives are crucial for AI-driven workforce preparation (George, A. S., 2023).
Leadership role	Transparent and proactive leadership is essential for guiding change and fostering a learning culture (Ransbotham et al., 2020).

Table 1: Key Research Themes and Findings in AI-Driven Workforce Transformation

Industry	**Finance**	**Education**	**Finance**	**High Tech**	**Government**	**Utility**	**Healthcare/ Education**	**Software**
Current Workforce Satisfaction	Challenges in hiring	Highly satisfied	Mixed due to pandemic	Not specified	Not ready for AI	Labor shortage	Not specified	Highly satisfied
AI Impact	Significant	Transformative	Upskilling required	Optimistic	Neutral	The solution to the labor gap	Subtle	Moderate
Types of Jobs Impacted	Customer service agents	Customer service roles	Repetitive tasks	Quality control, finance	Various clerical jobs	Routine tasks in water treatment	Educators, tutors	Software developers
Will AI Create Jobs?	Yes	Yes	Yes	Yes	Yes	Unclear	Mixed	Yes
Vulnerable Roles	Routine tasks	Data entry	Repetitive tasks	Call centers	Call centers	Meter reading	Not specified	Call center workers
New Skills	Operationalizing AI	Machine learning	Continuous learning	Data tagging	Adaptability	SCADA	N/A	Predictive analysis
Focus Areas	Education & Communication	Adaptive Learning & Awareness	Transparency & Education	Policy & Skills	Adaptability & Governance	Reskilling & Ethics	Ethical Concerns	Exploration & Productivity

Table 2: Sentiment of sample executives for the role of AI in the workforce and its development.

Predictive Analysis of Patients' Telemedicine Adoption in the Nashville Metropolitan Area – An Application of UTAUT Model

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Abstract

This quantitative predictive correlation study evaluated factors associated with the unified theory of acceptance and use of technology (UTAUT) that contribute to the patient's adoption of telemedicine. Specifically, the study determined whether the independent variables of performance expectancy, effort expectancy, social influence, and facilitating conditions significantly predicted healthcare patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area. The Nashville Metropolitan Area is renowned for its healthcare technology industry and highly respected healthcare community, yet many regional hospitals in the area have closed, making healthcare access difficult for many residents. The COVID-19 pandemic exacerbated healthcare access challenges. Telemedicine offers a solution to limited healthcare access, but solutions are only viable if patients are willing to adopt new technology. The literature review supporting this study identified knowledge gaps regarding patients' perceptions and attitudes toward telemedicine adoption and use Nashville Metropolitan Area. The survey data were analyzed using multiple linear regression analysis, and the findings indicated that performance expectancy, social influence, and facilitating conditions explained 50.8% of the variance in participants' behavioral intentions to adopt telemedicine. Further research is needed to examine specific telemedicine applications and patient experiences in various contexts. However, healthcare leaders and organizational decision-makers can use the study's findings to decide when telemedicine is most appropriate, increase telemedicine implementation success, and improve patient care services.

Keywords: COVID-19, Telemedicine adoption, Effort expectancy, Facilitating Conditions, Performance expectancy, Health expenditure, Nashville Metropolitan Area

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Predictive Analysis of Patients' Telemedicine Adoption in the Nashville Metropolitan Area – An Application of UTAUT Model

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1. INTRODUCTION

This study focused on the adoption of telemedicine in the Nashville Metropolitan Area following the COVID-19 pandemic. Specifically, the research aimed to determine whether factors associated with the unified theory of the acceptance and use of technology (UTAUT) significantly predict Nashville residents' decisions to adopt telemedicine. The state of Tennessee has experienced unique challenges associated with healthcare provision because of high rates of hospital closures and other factors limiting residents' access to healthcare (Letheren, 2021; Miller, 2023a, 2023b).

Telemedicine can potentially address challenges associated with limited healthcare access (DeGuzman et al., 2022; Hamnvik et al., 2022; Kahan et al., 2022; Rogers et al., 2022). However, the effective use of telemedicine relies on patients' technology acceptance (Almathami et al., 2020; Harst et al., 2019; So et al., 2021). This study explored whether factors like performance expectancy, effort expectancy, social influence, and facilitating conditions predict patients' decision-making when adopting telemedicine.

Information technology (IT) is changing the face of modern medicine. Technologies like artificial intelligence, connected healthcare devices, cloud computing, and telemedicine improve healthcare services and outcomes by increasing efficiency and convenience (Garai et al., 2019; Kaplan, 2020; Tian et al., 2019). However, these technologies can only improve health outcomes if they are adopted by patients and healthcare professionals (Almathami et al., 2020). This study focused on the adoption of telemedicine among patients in the Nashville Metropolitan Area.

Telemedicine refers to the use of telecommunications and IT to provide healthcare services virtually over a distance with a patient in one location and a healthcare professional in another location (Bittmann et al., 2023; Kahan et al., 2022; Udsen et al., 2023). Telemedicine also encompasses virtual coordination between primary care physicians, hospital staff, and specialists (Seguí et al., 2020). Healthcare providers are using telemedicine to treat an increasing number of health problems, including diabetes, substance abuse, and epilepsy (Hazenberg et al., 2020; Ludvigsson, 2021; Shakir & Wakeman, 2021; von Wrede et al., 2020).

Despite the advantages of telemedicine, some barriers to implementation do exist. Patients and healthcare providers can resist telemedicine for various reasons (Amos et al., 2022; Beheshti et al., 2022). Patients can resist telemedicine because of concerns about technological literacy, data privacy, and quality of care (Fieux et al., 2020; Kruse et al., 2021; Nittari et al., 2020). Technologies cannot be effective or beneficial if users do not adopt them (Almathami et al., 2020; Harst et al., 2019; So et al., 2021). Thus, it is important to understand the factors influencing adoption and use when new technologies are implemented.

The general research problem this study focused on was the lack of research on the factors influencing telemedicine adoption in the United States in areas with limited healthcare access. Especially, Tennessee has experienced many recent hospital closures, and COVID-19 further limited in-person access to physicians and traditional healthcare. Nevertheless, the Nashville Metropolitan Area is renowned for its healthcare technology industry and a highly respected healthcare community (Frist, 2021). For these reasons, the Nashville Metropolitan Area provides a unique opportunity to study telemedicine adoption to determine the most important factors to patients.

Previous telemedicine studies have focused on research topics that are narrower or peripheral to the present topic. For example, some researchers focused on telemedicine adoption in other countries (Gu et al., 2021; Siripipatthanakul et al., 2023; von Wrede et al., 2020). Others only considered healthcare providers' acceptance and use of telemedicine (Garavand et al., 2022; Rouidi et al., 2022; Shiferaw et al., 2021). However, a gap exists in the literature because no studies focus on general telemedicine adoption in the Nashville Metropolitan Area after the COVID-19 pandemic.

Findings from this study could benefit medical practices and ambulatory settings where telemedicine is used. Walk-in and outpatient clinics can use telemedicine as a triaging tool (Philips et al., 2019). Organizational leaders could use the findings to understand the role of patient acceptance when implementing telemedicine services. It is also possible that the findings could alleviate physicians' concerns that present barriers to telemedicine use.

In addition to healthcare professionals and organizations, the present study has the potential to benefit patients. Patients considering telemedicine could use the study's findings to increase their awareness and understanding of its benefits while examining their expectations about the effort it requires and how it could improve their health outcomes. The findings may be specifically helpful to Tennessee residents, specifically those in the Nashville Metropolitan Area and other regions in the United States where access to traditional healthcare services is becoming more limited.

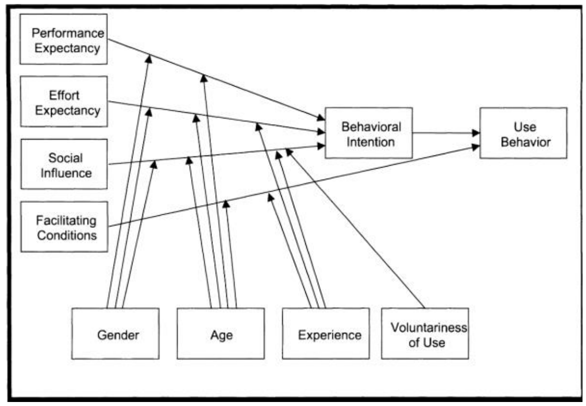
2. THEORETICAL FRAMEWORK

This study used Venkatesh et al.'s (2003) original UTAUT model as a theoretical framework to understand healthcare patients' perspectives and behaviors toward telemedicine adoption in the Nashville Metropolitan Area. The UTAUT is a modification of the technology acceptance model (TAM), enabling researchers to determine levels of users' acceptance and use of new technology. Using the UTAUT as a framework allows researchers to study users' perceptions of a specific technology, and the value of the technology can be established based on the user's needs (Drehlich et al., 2020). Figure 1 presents the UTAUT model as designed by Venkatesh et al. (2003).

As indicated in Figure 1, the UTAUT's main independent variables are performance expectancy, effort expectancy, social influence, and facilitating conditions. Venkatesh et al. (2003) theorized that these variables significantly influenced behavioral intentions to use technology and actual use behavior. Additionally, gender, age, experience, and voluntariness of use are moderating variables affecting the main variable relationships in the UTAUT. Venkatesh et al. (2003) tested their model and found that the independent variables explained 70% of the variance in technology usage intentions.

Figure 1 : The UTAUT Model

Note. From "User Acceptance of Information Technology: Toward a Unified View," by V. Venkatesh et al., 2003, MIS Quarterly



The present study also modified the UTAUT model by focusing on direct relationships between the predictor variables (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) and patients' use behavior, defined as telemedicine adoption. Additionally, the moderating variables of gender, age, experience, and voluntariness of use were excluded from the present analysis. The exclusion of the moderating variables was based on the study's aim to determine whether significant relationships existed between the independent variables and telemedicine use. Future research can examine moderating influences after significance is established in the primary relationships.

The four primary relationships that this research aimed to establish were the relationships between performance expectancy, effort expectancy, social influence, and facilitating conditions and the dependent variable of telemedicine adoption among patients in the Nashville Metropolitan Area. Performance expectancy refers to an individual's belief that using technology would improve performance outcomes (Venkatesh et al., 2003). It was expected that people would be more likely to use telemedicine if they believed it would improve health outcomes. Effort expectancy refers to how easy technology is to use (Venkatesh et al., 2003). It was expected that people would be more likely to use telemedicine if they felt it would be easy to use. Social influence refers to the belief that influential people (e.g., authority figures, colleagues, and family members) feel technology should be used. It was expected that patients whose doctors, friends, and family supported telemedicine would be more likely to use it. Facilitating conditions refers to the availability of technical infrastructure that supports the use of technology. It was expected that patients who believed they had the necessary infrastructure and support would be more likely to use telemedicine.

3. LITERATURE GAP AND THE PRESENT STUDY'S CONTRIBUTION

The literature review indicated that despite extensive research focused on telemedicine, more research is needed. Many studies were evaluated during the planning and completion of this study. The literature review served an important purpose in identifying research gaps. Telemedicine is an extremely popular research topic among healthcare and technology adoption researchers (Almathami et al., 2020; Garavand et al., 2022; Hazenberg et al., 2020). The vast number of systematic literature reviews on different aspects of telemedicine illustrated the great diversity and interest in this topic (Atmojo et al., 2020; Kavandi & Jaana, 2020; Kruse & Heinemann, 2022). Despite the thousands of studies on telemedicine, recent systemic reviews illustrate that gaps remain in scholars' understanding of many aspects of telemedicine application and use.

Systematic reviews by Almathami et al. (2020) and Kruse and Heinemann (2022) reviewed research on facilitators and barriers to telemedicine adoption. One of the biggest differences between the two reviews was that Kruse and Heinemann (2022) specifically looked at barriers and facilitators after the onset of the COVID-19 pandemic. Other scholars like Garavand et al. (2022) and Kavandi and Jaana (2020) oriented their reviews toward specific stakeholder groups. Garavand et al. (2022) studied physicians' telemedicine acceptance, while Kavandi and Jaana (2020) narrowed the focus of their review to elderly patients. Other systematic reviews focused on using telemedicine to treat specific types of illnesses. Hazenberg et al. (2020) systematically reviewed using telemedicine to treat diabetic conditions, and Zangani et al. (2022) reviewed global mental health studies using telemedicine. Several systematic reviews even focused exclusively on articles using the TAM and UTAUT as telemedicine adoption frameworks (Kavandi & Jaana, 2020; Rouidi et al., 2022).

Systematic reviews of existing studies are very valuable to researchers because they aggregate the findings from similar studies and enable convenient comparison of methods and findings. However, these reviews also have significant limitations. Systematic reviews rely on secondary data and findings reported in primary studies. Authors of systematic reviews do not independently verify findings in the studies they review. Despite this significant limitation, the systematic reviews on telemedicine research included in this review highlighted the lack of studies focused on patient adoption of telemedicine in the Nashville Metropolitan Area following the onset of the COVID-19 pandemic. The absence of similar studies focused on this population represents a gap in the body of knowledge addressed by examining whether performance expectancy, effort expectancy, social influence, and facilitating conditions could significantly predict the behavioral intention to adopt telemedicine in the study's target population.

The literature also included studies specific to the Nashville Metropolitan Area. Mercer and Newbrough's (1967) study illustrated how healthcare access in the city has been a decades-long concern, and Carr et al. (2004) studied healthcare entrepreneurship in Nashville's healthcare industry during the early 2000s. Haddadin et al. (2022) and Stubblefield et al. (2021) focused on specific healthcare outcomes following the COVID-19 pandemic. Nashville was even a focal point in Marks's (2020) article on telemedicine use in orthopedics. These studies illustrate Nashville's unique role in the healthcare industry as a hub for innovation and demonstrate that the city has been healthcare research setting for decades. However, none of these studies address this study's aims or provide information on the factors influencing telemedicine adoption.

4. RESEARCH METHODS AND FINDINGS

This study used the UTAUT framework to define the constructs and collected targeted population responses via a survey instrument and questionnaire based on Venkatesh et al.'s (2003) research. The survey was adapted with permission to capture users' behavior and experience towards telemedicine, and the responses were categorized using a Likert scale.

Table A: Modified Questions aligning with Constructs and Survey Items from Venkatesh et al. (2003)

Construct	Original Questions	Modified Questions
	1. I would find the system useful in my job. 2. Using the system enables me to accomplish tasks more quickly. 3. Using the system increases my productivity. 4. If I use the system, I will increase my chances of getting a raise.	1. I would find telemedicine useful in managing my healthcare outcomes. 2. Using telemedicine enables me to improve my healthcare outcomes. 3. Using telemedicine saves time when managing my healthcare. 4. If I use telemedicine, I will increase my chances of having positive health outcomes.
Effort Expectancy	1. My interaction with the system would be clear and understandable. 2. It would be easy for me to become skillful at using the system. 3. I would find the system easy to use. 4. Learning to operate the system is easy for me.	1. The process of using telemedicine to manage my healthcare would be clear and understandable. 2. It would be easy for me to become skillful at using telemedicine. 3. I would find telemedicine easy to use when managing my healthcare. 4. Using telemedicine is easy for me.
Social influence	1. People who influence my behavior think that I should use the system. 2. People who are important to me think that I should use the system. 3. The senior management of this business has been helpful in the use of the system. 4. In general, the organization has supported the use of the system.	1. People who influence my personal behavior think that I should use telemedicine. 2. People in my life who are important to me think that I should use telemedicine. 3. My healthcare providers have suggested using telemedicine to manage my healthcare. 4. In general, my friends and family have supported using telemedicine.
Facilitating conditions	1. I have the resources necessary to use the system. 2. I have the knowledge necessary to use the system. 3. The system is not compatible with other systems I use. 4. A specific person (or group) is available for assistance with system difficulties.	1. I have the resources necessary to use telemedicine. 2. I have the knowledge necessary to use telemedicine. 3. Telemedicine is compatible with other technologies I use. 4. I can get help from others when I have difficulties using telemedicine.
Behavioral intention	1. I intend to use the system in the next <n> months. 2. I predict I would use the system in the next <n> months. 3. I plan to use the system in the next <n> months.	1. I intend to use telemedicine in the future. 2. I predict I will use telemedicine in the future. 3. I plan to use telemedicine in the future.

The questionnaire targeted Nashville adults who have used telemedicine services during the last 2 years. The aim was to understand consumer behaviors toward adoption and technology challenges. Table A below displays the survey questionnaire modified to align with original survey items from Venkatesh et al. (2003)

This study used a predictive correlational research design to study patients' telemedicine adoption in the Nashville Metropolitan Area. Predictive correlational designs enable researchers to forecast outcomes based on correlations between predictor (i.e., independent) and outcome (i.e., dependent) variables. The study's main predictor variables were performance expectancy, effort expectancy, social influence, and facilitating conditions.

This study used the UTAUT framework to define the constructs and collected targeted population responses via a survey instrument and questionnaire based on Venkatesh et al.'s (2003) research. The survey was adapted with permission to capture users' behavior and experience towards telemedicine, and the responses were categorized using a Likert scale. The questionnaire targeted Nashville adults who have used telemedicine services during the last 2 years. The aim was to understand consumer behaviors toward adoption and technology challenges.

This study used multiple linear regression modeling to analyze the survey data. The analysis determined the significance of correlations between the independent and dependent variables to identify factors contributing to patients' telemedicine adoption in the Nashville Metropolitan Area.

The following four research questions were answered by testing a corresponding set of null and alternative hypotheses- 1. To what extent does performance expectancy predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area? 2. To what extent does effort expectancy predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area? 3. To what extent does social influence predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area? 4. To what extent do facilitating conditions predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area?

The study included N = 150 participants living in the Nashville Metropolitan Area. Pollfish, a third-party survey facilitator, provided a sample frame and selected participants randomly from database members who fit the study's inclusion and exclusion criteria. These criteria required participants to: (a) live in Nashville, Davidson, Murfreesboro, or Franklin, Tennessee; (b) have used telemedicine in the last 2 years since the onset of COVID-19; and (c) be 18 years of age or older. No additional gender, race, or economic factors were used to limit participation.

Participants shared demographic data used to describe the sample. This data included gender, age, experience level, and the voluntariness of their telemedicine use. The sample was split fairly evenly based on gender, with n = 65 female (43.3%) and n = 73 male participants (48.7%). Next, the survey administered by Pollfish asked participants to indicate their age by selecting an age range from 10 options: 18–25, 26–30, 31–35, 36–40, 41–45, 46–50, 51–55, 56–60, 61–65, and Over 65. The largest age cohorts were participants ages 31–35 (19.3%), 36–40 (18%), and 41-50 (18%). The smallest age cohorts were participants ages 61–65 (2.7%) and 46–50 (4%).

Table B: Sample Distribution Based on Experience

Note. N = 150. The sample did not include missing responses.

Experience Using Telemedicine	*N*	%
Very inexperienced	11	7.3
Inexperienced	10	6.7
Somewhat inexperienced	15	10.0
Neither	16	10.7
Somewhat experienced	56	37.3
Experienced	31	20.7
Very Experienced	11	7.3
Total	150	100.0

Another demographic data point collected from participants was their experience using telemedicine. All participants were required to have used telemedicine at least once in the 2 years since COVID-19. This requirement was to ensure that participants were minimally familiar with telemedicine technology in one form or another. Participants rated their experience level using telemedicine on a 7-point Likert scale ranging from 1 (*Very inexperienced*) to 7 (*Very experienced*). The sample was somewhat evenly distributed based on experience level. The same number of participants indicated they were either very inexperienced or very experienced (*n* = 11, 7.3%). The two largest experience cohorts within the sample were individuals identifying as somewhat experienced (*n* =56, 37.3%) and individuals identifying as experienced (*n* = 31, 20.7%). Table B provides a full sample distribution based on experience level using telemedicine.

Additional characteristic evaluated as part of the sample description was the voluntariness of telemedicine use. COVID-19 resulted in the closure or restriction of many healthcare organizations and services, and these closures and restrictions forced some patients and healthcare providers to implement telemedicine options. This study did not focus directly on the issue of voluntary vs. forced telemedicine use. Instead, this question was included to combat the assumption that telemedicine use is always voluntary. Most participants (81.3%) indicated that their telemedicine use was voluntary. However, almost 1 in 5 participants (n = 28, 18.7%) indicated that their telemedicine use was involuntary. Table C presents the sample distribution based on voluntariness of use.

The full sample included N =150 participants. The minimum number of participants required for the analysis, determined by an a priori G*Power analysis, was N = 129. However, a minimal number of additional participants were sampled to ensure that the sample would be large enough if the elimination of outliers or incomplete responses were required.

Table C: Sample Distribution Based on Voluntariness of Use

Note. N = 150. The sample did not include missing responses.

Voluntariness of Use	N	%
Yes	122	81.3
No	28	18.7
Total	150	100.0

Descriptive statistics were used to catalog and evaluate the dataset. Behavioral intention had the highest M (5.58) and SD (1.454) values for all the constructs. Social influence had the lowest M (4.51) score, and facilitating conditions had the lowest SD (1.083) of the constructs. Cronbach's alpha coefficients determined that behavioral intention had the highest reliability coefficient (ɑ = 0.837), and facilitating conditions had the lowest reliability coefficient (ɑ = 0.7). Scores above 0.7 meet the standard of acceptability, so the instrument was suitable for examining telemedicine adoption among patients in the Nashville Metropolitan Area.

Research Question One

Research Question One asked, to what extent does performance expectancy predict patients' telemedicine adoption in the Nashville Metropolitan Area? Testing a pair of corresponding hypotheses answered this question. The hypotheses were as follows:

H01. Performance expectancy does not significantly predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area.

Ha1. Performance expectancy significantly predicts patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area.

The multiple linear regression analysis used to test the hypotheses for Research Question One indicated that performance expectancy significantly predicts Nashville Metropolitan Area residents' behavioral intentions to adopt telemedicine (β = 0.381, t(145) = 4.760, p < 0.001). The relationship between the variables was positive, indicating that as performance expectancy increased, behavioral intentions to adopt telemedicine increased, and the relationship was significant. Based on these findings, the null hypothesis was rejected.

Research Question Two

Research Question Two asked, to what extent does effort expectancy predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area? Testing a pair of corresponding hypotheses answered this question. The hypotheses were as follows:

H02. Effort expectancy does not significantly predict patients' telemedicine adoption in the Nashville Metropolitan Area.

Ha2. Effort expectancy significantly predicts patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area.

The multiple linear regression analysis used to test the hypotheses for Research Question Two indicated that effort expectancy did not significantly predict Nashville Metropolitan Area residents' behavioral intentions to adopt telemedicine (β = -0.018, t (145) = -0.214, p = 0.831). The negative relationship between the variables indicated that behavioral intentions to adopt telemedicine decreased as effort expectancy increased. However, based on the p-value, the negative relationship was not significant, suggesting effort expectancy was not a driving factor in telemedicine adoption. As a result of these findings, the null hypothesis was not rejected.

Research Question Three

Research Question Three asked, to what extent does social influence predict patients' behavioral intent to adopt telemedicine in the Nashville

Metropolitan Area? Testing a pair of corresponding hypotheses answered this question. The hypotheses were as follows:

H03. Social influence does not significantly predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area.

Ha3. Social influence significantly predicts patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area.

The multiple linear regression analysis used to test the hypotheses for Research Question Three indicated that social influence significantly predicts Nashville Metropolitan Area residents' behavioral intentions to adopt telemedicine (β = 0.252, t (145) = 4.025, p < 0.001). The positive relationship between the variables indicated that behavioral intentions to adopt telemedicine increased as social influence increased. The p-value indicated that the relationship was significant, and the null hypothesis should be rejected.

Research Question Four

Research Question Four asked, to what extent do facilitating conditions predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area? Testing a pair of corresponding hypotheses answered this question. The hypotheses were as follows:

$H_0$4. Facilitating conditions do not significantly predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area.

H_a4. Facilitating conditions significantly predict patients' behavioral intent to adopt telemedicine in the Nashville Metropolitan Area.

The multiple linear regression analysis used to test the hypotheses for Research Question Four indicated that facilitating conditions significantly predict Nashville Metropolitan Area residents' behavioral intentions to adopt telemedicine (β = 0.299, *t* (145) = 3.846, *p* < 0.001).

Table C: Regression Model Coefficients

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, BI = behavioral intention

Unstandardized Coefficients		Standardized Coefficients		
B	*SE*	β	*t*	*p*
Constant	0.737	0.419		0.080
PE	0.395	0.083	0.381	0.000
EE	-0.020	0.092	-0.018	0.831
SI	0.239	0.059	0.252	0.000
FC	0.336	0.087	0.299	0.000

Table D: Hypothesis results

Note. A *p* < 0.05 threshold was used to determine significance.

H#	Predictor-outcome variable relationship	*p*-value	Result
1	Performance expectancy -> Behavioral intention	< 0.001	Reject the Null
2	Effort expectancy -> Behavioral intention	0.831	Retain the Null
3	Social influence -> Behavioral intention	< 0.001	Reject the Null
4	Facilitating conditions -> Behavioral intention	< 0.001	Reject the Null

The positive relationship between the variables indicated that behavioral intentions to adopt telemedicine increased as positive perceptions of facilitating conditions increased. The *p*-value indicated that the relationship was significant, and the null hypothesis should be rejected.

Table C presents the regression model coefficients used to determine the extent and significance of the relationship between effort expectancy and behavioral intention, including the β and *p*-values. Table D summarizes the hypothesis results used to answer the study's research questions.

5. DISCUSSION AND IMPLICATIONS

This study evaluated telemedicine adoption in the Nashville Metropolitan Area using the unified theory of acceptance and use of technology (UTAUT) as a theoretical lens. Telemedicine offers many benefits to patients living in areas with limited healthcare access (DeGuzman et al., 2022; Hamnvik et al., 2022; Kahan et al., 2022). High rates of hospital closures in Tennessee and ongoing physician shortages suggest that telemedicine could be a useful strategy for healthcare provision in the area (Hooker et al., 2022; Letheren, 2021; Miller, 2023a, 2023b). However, the effective use of telemedicine relies on patients' acceptance of technology (Almathami et al., 2020; Harst et al., 2019; So et al., 2021). This study explored whether factors like performance expectancy, effort expectancy, social influence, and facilitating conditions predict patients' decision-making when adopting telemedicine

Findings from Research Question One indicated that performance expectancy significantly predicted behavioral intentions to use telemedicine. Thus, the null hypothesis was rejected. The positive significant relationship between performance expectancy and behavioral intention meant that participants who believed using telemedicine would improve their health outcomes were more likely to intend to use telemedicine.

This study was a predictive correlation, meaning that the changes in performance expectancy can be used to predict changes in behavioral intentions. However, causality cannot be inferred, and it is improper to conclude that participants' belief that telemedicine would improve health outcomes caused the increased behavioral intention to adopt the technology. The findings aligned with the UTAUT model, which anticipates a positive predictive relationship between performance expectancy and behavioral intention (Chao, 2019).

The findings also echoed with similar technology adoption research showing significant positive relationships between performance expectancy and behavioral intention (Alabdullah et al., 2020; Rouidi et al., 2022). The findings indicate that a telemedicine application has a greater chance of being adopted and used if it helps patients manage their healthcare treatments, improves their health outcomes, saves time, or improves their health. Healthcare professionals should consider these factors when providing telemedicine options to patients. Telehealth developers can benefit from the study's findings by understanding that performance is a key requirement for adoption. Finally, organizational leaders and decision-makers should consider whether telemedicine improves healthcare outcomes before implementing new technologies. If stakeholders perceive telemedicine as useful, the technology will be more likely to be adopted by patients, and the implementations will be more successful.

Findings from Research Question Two indicated that effort expectancy did not significantly predict behavioral intentions to use telemedicine. The relationship between effort expectancy and behavioral intention was negative, indicating that participants who believed telemedicine was difficult to use were less likely to intend to use telemedicine. However, the relationship was not statistically significant, and the null hypothesis was retained. The lack of significance meant that effort expectancy could not be used to predict changes in behavioral intentions toward telemedicine adoption.

Effort expectancy refers to whether a technology can be mastered quickly and easily (Rouidi et al., 2022). A positive relationship means that users who believe technology will be easy to use are more likely to use it than users who feel telemedicine will be difficult to use (Beh et al., 2021). Stakeholders must recognize that the effort associated with using technology is not automatically a critical element in the successful use of telemedicine.

Healthcare professionals do not need to recommend the most basic or easy-to-use applications. Instead, they can promote applications with the greatest utility and chance to improve healthcare outcomes. Patients may not be as concerned about how easy a system is to use because technology makes most actions easier. Therefore, telehealth developers can focus on utility over complexity. Furthermore, when faced with a choice, organizational decision-makers can choose a more complex telemedicine application with greater performance metrics over a simpler app with fewer healthcare benefits.

Findings from Research Question Three indicated that social influence significantly predicted behavioral intentions to use telemedicine. The null hypothesis was rejected as a result. The positive significant relationship between social influence and behavioral intention meant that participants who believed others felt technology was important were more likely to intend to use telemedicine.

Social influence refers to whether a user feels other influential people in their lives feel using a technology is important (Venkatesh et al., 2003, 2012). In the UTAUT, social influence reflects whether influential and important people like friends and family believe technology should be used (Joa & Magsamen-Conrad, 2021).

The present study's findings highlight the importance of support from friends and family and expert opinions from healthcare professionals. The results align with the UTAUT and research conducted by Liu et al. (2019), Petersen et al. (2020), and Zhou et al. (2019). In each study, social influence was a strong factor in technology adoption. Liu et al. (2019) focused on physical activity. Petersen et al. (2020) examined mobile health application adoption by diabetes patients, and Zhou et al. (2019) studied nurses' adoption of electronic information management systems. These studies illustrate that social influence is a factor in various contexts, even among differing stakeholder groups.

For healthcare professionals, the present study's findings highlight the power of their social influence when recommending a telemedicine application. Most patients rely on and respect healthcare professionals as authority figures, and their recommendations can be influential. Healthcare providers should use their authority and social influence in ways that avoid damaging the provider-patient relationship.

Developers must recognize the importance of all stakeholders when designing applications, and organizations seeking to implement telemedicine options into their care services should evaluate attitudes toward technology among physicians and patients during the planning stages

Findings from Research Question Four indicated that facilitating conditions significantly predicted participants' behavioral intentions to use telemedicine. The positive significant relationship between facilitating conditions and behavioral intention meant that participants who had access to supportive infrastructure and systems were more likely to intend to use telemedicine.

Facilitating conditions refer to the infrastructure and support systems available to technology users (Shiferaw et al., 2021). Napitupulu et al. (2021) noted that facilitating conditions in healthcare contexts like telemedicine can refer to Internet access and smartphone or computer use. Rouidi et al. (2022) systematically reviewed 12 studies that included facilitating conditions as a variable. They reported that 11 of the 12 articles found support for facilitating conditions as a strong predictor of technology adoption.

Healthcare professionals should ensure patients can access the resources necessary to use telemedicine before recommending these care alternatives. Telemedicine developers should consider designing applications compatible with devices using diverse operating systems to broaden their accessibility and attract users of Apple and Android devices. Organizational leaders should consider hiring dedicated staff to support patient and physician technical needs during telemedicine implementation. These suggestions could potentially improve patients' telemedicine experiences and promote adoption.

6. LIMITATIONS OF THE STUDY

This study had several limitations related to sampling methods and aspects of the research design. The study's focus on the Nashville Metropolitan Area was the first limitation associated with sampling. The area was chosen because even though the Nashville Metropolitan Area is renowned for its influence in the healthcare industry, Tennessee faces serious healthcare access challenges due to hospital closures and physician shortages (Frist, 2021; Letheren, 2021; Miller, 2023a, 2023b). The unique characteristics of the research setting mean that the findings may not be easily generalized to other areas in the United States

Another limitation associated with sampling was the choice of simple random sampling instead of stratified random sampling. Research has shown that older adults adopt technology at lower rates than younger adults (Mitzner et al., 2019). However, without a stratified sample, it was impossible to determine whether age significantly moderated the relationships between performance expectancy, social influence, facilitating conditions, and behavioral intentions to adopt telemedicine.

Another limitation was using a third-party survey company to gather data for this quantitative analysis. Pollfish conducted the survey, which limited the participants to individuals who make up Pollfish's panel of voluntary survey takers. The most technology-resistant individuals are probably not members of an online survey panel. For this reason, some level of selection bias should be expected (Nayak & Narayan, 2019).

The cross-sectional, non-experimental research design was also a limitation as they meant that the findings did not show any change in participants' behavioral intentions to adopt telemedicine over time. A final limitation involved the UTAUT as a theoretical framework. Using the UTAUT meant that only four independent variables were examined as predictors of telemedicine adoption. Other factors like privacy, fear, or cybersecurity may have influenced participants' telemedicine adoption (Chu et al., 2021; Fieux et al., 2020; Lateef, 2020).

7. IMPLICATIONS FOR FUTURE STUDY

An analysis of the study's limitations highlights the study's many implications for future research. Future research can extend the application of this study's findings by changing the target population and sampling procedures. Fahs (2020) noted that healthcare access varies drastically based on geographic location, and Rhyan et al. (2020) found that patients in rural areas used telemedicine at higher rates than their urban counterparts. A quantitative, comparative study focused on regional or population-density differences within the United States would illustrate how telemedicine adoption varies and identify potential factors influencing that variance.

Employing a longitudinal research design would allow researchers to develop a more detailed understanding of the telemedicine adoption process. This study only looked at participants' experiences, beliefs, and attitudes after they had used telemedicine. Using a cross-sectional approach meant this study could not infer causal relationships between the variables (Spector, 2019). A mixed-methods approach that collected data at several points in the adoption process (e.g., before, during, and after use) would enable researchers to document participants' experiences in detail, identify adoption barriers and incentives, and explain changes in participants' attitudes and intentions toward telemedicine adoption.

Finally, future research should consider telemedicine adoption through additional theoretical lenses. This study used the UTAUT as a framework for evaluating telemedicine adoption. However, the variables of performance expectancy, social influence, and facilitating conditions only explained 50% of the variance in participants' behavioral intentions to use telemedicine. Other factors like trust, safety, and digital literacy could affect patients' willingness to adopt healthcare-related technologies (Fieux et al., 2020; Luciano et al., 2020; Nittari et al., 2020). Researchers could use the protection motivation theory or the technology threat avoidance theory to explore the impact of additional variables. Alternatively, researchers could modify the UTAUT model by adding constructs like trust, security awareness, and digital literacy. Such an approach would provide a more thorough understanding of the antecedents of telemedicine adoption among patients.

8. SUMMARY

Many studies were evaluated during the planning and completion of this study. The literature review served an important purpose in identifying research gaps. Telemedicine is an extremely popular research topic among healthcare and technology adoption researchers (Almathami et al., 2020; Garavand et al., 2022; Hazenberg et al., 2020). The vast number of systematic literature reviews on different aspects of telemedicine illustrated the great diversity and interest in this topic (Atmojo et al., 2020; Kavandi & Jaana, 2020; Kruse & Heinemann, 2022). Despite the thousands of studies on telemedicine, recent systemic reviews illustrate that gaps remain in scholars' understanding of many aspects of telemedicine application and use.

Systematic reviews by Almathami et al. (2020) and Kruse and Heinemann (2022) reviewed research on facilitators and barriers to telemedicine adoption. One of the biggest differences between the two reviews was that Kruse and Heinemann (2022) specifically looked at barriers and facilitators after the onset of the COVID-19 pandemic. Other scholars like Garavand et al. (2022) and Kavandi and Jaana (2020) oriented their reviews toward specific stakeholder groups. Garavand et al. (2022) studied physicians' telemedicine acceptance, while Kavandi and Jaana (2020) narrowed the focus of their review to elderly patients. Other systematic reviews focused on using telemedicine to treat specific types of illnesses. Hazenberg et al. (2020) systematically reviewed using telemedicine to treat diabetic conditions, and Zangani et al. (2022) reviewed global mental health studies using telemedicine. Several systematic reviews even focused exclusively on articles using the TAM and UTAUT as telemedicine adoption frameworks (Kavandi & Jaana, 2020; Rouidi et al., 2022).

Systematic reviews of existing studies are very valuable to researchers because they aggregate the findings from similar studies and enable convenient comparison of methods and findings. However, these reviews also have significant limitations. Systematic reviews rely on secondary data and findings reported in primary studies. Authors of systematic reviews do not independently verify findings in the studies they review. Despite this significant limitation, the systematic reviews on telemedicine research included in this review highlighted the lack of studies focused on patient adoption of telemedicine in the Nashville Metropolitan Area following the onset of the COVID-19 pandemic. The absence of similar studies focused on this population represents a gap in the body of knowledge addressed by examining whether performance expectancy, effort expectancy, social influence, and facilitating conditions could significantly predict the behavioral intention to adopt telemedicine in the study's target population.

The literature also included studies specific to the Nashville Metropolitan Area. Mercer and Newbrough's (1967) study illustrated how healthcare access in the city has been a decades-long concern, and Carr et al. (2004) studied healthcare entrepreneur Nashville's healthcare industry during the early 2000s. Haddadin et al. (2022) and Stubblefield et al. (2021) focused on specific healthcare outcomes following the COVID-19 pandemic. Nashville was even a focal point in Marks's (2020) article on telemedicine use in orthopedics. These studies illustrate Nashville's unique role in the healthcare industry as a hub for innovation and demonstrate that the city has been healthcare research setting for decades. However, none of these studies address this study's aims or provide information on the factors influencing telemedicine adoption

Patients constitute important stakeholders in the adoption and implementation of telemedicine (Atmojo et al., 2020; Darrat et al., 2021; Ikram et al., 2020). Telemedicine technologies cannot be effective or beneficial if users refuse to adopt them (Almathami et al., 2020; Harst et al., 2019; So et al., 2021). Therefore, understanding the factors that predict patients' behavioral intentions to adopt telemedicine is critical to successful implementations. This study utilized the UTAUT

as a theoretical framework to examine patients' intent to use telemedicine in the Nashville Metropolitan Area.

This study addressed gaps in the literature by analyzing data from N =150 residents in the Nashville Metropolitan Area using multiple linear regression. The analysis determined that performance expectancy, social influence, and facilitating conditions significantly predicted 50.8% of the variance in patients' intention to adopt telemedicine. The findings suggest that healthcare decision-makers and organizational leaders can improve telemedicine adoption by emphasizing how telemedicine can improve healthcare outcomes, promoting positive social attitudes toward telemedicine applications, and providing infrastructure and resources that support telemedicine adoption. While more research is needed to explore telemedicine adoption in specific settings, this study's findings indicate that most telemedicine use is voluntary and supported by positive performance, social, and technological factors

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Are Employers Resistant to Change the Traditional Work Environment? A Pilot Study of Employer Perceptions on Remote Work and Shortened Work Weeks

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Abstract

The COVID-19 pandemic forced organizations to re-visit changes and trends in the workplace environment, including how to recruit and retain new employees. In particular, how are employers adjusting to prospective employees looking for remote and hybrid working conditions along with the option of more flexible schedules, including the possibility of a shortened work week? This study focused on two specific trends: remote work and shortened work week. A survey was sent to business leaders and hiring managers in the local community. A similar survey was conducted to upper-class students looking for internships and full-time employment opportunities. The results show that while employers may recognize the possible benefits of a flexible work environment, there are also disadvantages to this type of flexibility. Many of the study respondents reported they are open to implementing a hybrid work environment, but they are unlikely to implement fully remote work or shortened work weeks.

Keywords: Remote Work, Hybrid Work, Shortened Work Week, Covid, Employee Recruitment, Retention

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Are Employers Resistant to Change the Traditional Work Environment? A Pilot Study of Employer Perceptions on Remote Work and Shortened Work Weeks

Phillip Kim, Rachel Harker and Jennifer Breese

1. INTRODUCTION

The COVID-19 pandemic was a worldwide calamity that uprooted the way business' function. The traditional business model had to be adjusted in the face of lockdowns and uncertainty. During this time, there were many shifts in the standards of workplaces, and some of these changes altered the way that employees expected their working lives to be (Surma et al., 2021). In particular, it changed the way employees worked and what their expectations were. It also changed the way managers recruited, directed, and retained their workforce (Agba et al., 2020; O'Rourke, 2021). While the effects of the pandemic continue to persist, much of the research continues to lean toward employee data. This study focuses more on how employers and hiring managers are responding to the changing landscape of employee expectations.

The traditional business model was turned on its head as employers tried to create a "new normal" working environment for their existing employees, global partners, suppliers, regulatory agencies, and their customers. The "Great Lockdown" caused by the pandemic pushed many employers to provide completely new approaches to handling the average workday. These new approaches and tools have remained in place for many businesses even after the pandemic has concluded (Reuschke & Felstead, 2020). In 2021, the "Great Resignation" suggested to many employers that the traditional business model was no longer desirable to the majority of employees (Richter, 2022). This subtle but significant shift in power places the onus on employers to adjust to the increasing needs of the employees but also forces management to look at their existing practices to ensure a more efficient and productive workforce.

This research looks at two major trends that were spurred by the pandemic, and how these trends have altered both the expectations of employees entering the workforce and those of the employers potentially hiring these employees. The first major change that is examined is the trend towards remote and hybrid working conditions that were started by government shutdowns. Remote working conditions are specified as being when an employee works solely from home. Hybrid working conditions are when an employee works an equal balance from home and in-person at the office. The second topic considered is creating a more flexible work schedule. One component of this is creating a shortened workweek or 4-day work week. This study collected responses from both employers looking to fire the next generation of employees and upper-class students preparing for full-time employment and internship opportunities.

2. LITERATURE REVIEW

One of the prominent changes during the height of the pandemic was a resurgence of remote work or a hybrid mix between working in-person and virtually from any location. When the global pandemic spread across organizations, many companies had to come up with contingency plans to rapidly adapt to the government curfews and closures, supply chain disruptions, employee absenteeism, and high sickness rates (Hou et al., 2021). A viable option that arose during this time for many companies was to send their employees home and have them work remotely (Diab-Bahman & Al-Enzi, 2020). This solution seemed suitable for more traditional office jobs, but it did not encompass all working situations. For example, over 40% of jobs involving finance and business industries increased their remote/hybrid working occurrences because of the pandemic. In comparison, those working in transportation, mining, and food services were unable to switch to remote working scenarios at all (Dalton & Groen, 2022). This transition to remote/hybrid working has remained a permanent aspect of many companies that switched over to it during the pandemic. Before the outbreak, 23% of those surveyed revealed that they were able to work remotely. In 2022, over 60% of USA workers who believed that their jobs were able to be done remotely were found to be working from home at least some of the time (Parker, Horowitz, & Minkin, 2022).

Advantages for Employers and Employees

The adapted working environment that employees and employers were forced into had many advantages for both parties. One of the largest advantages of teleworking during the outbreak was increased safety for employees and managers alike. COVID was a very turbulent time that was filled with uncertainty and huge health concerns. This distanced working environment helped to reduce the number of people who got exposed to COVID and it also helped to bolster the wellbeing of employees during this challenging time.

Remote working not only prevented people from getting sick, but it also opened the door to greater diversity for those who were not able to work in a traditional working environment. Those with disabilities or illnesses or even those with young children were now offered a different kind of working environment that could fit their unique situations.

Another great benefit that working from home created was increased flexibility for employees. With this style of work, employees are able to have more flexibility and control over their own hours, their own breaks, etc. This can help employees who have other responsibilities and schedules (Diab-Bahman & Al-Enzi, 2020). Some studies suggest that remote working can help employees to be even more productive than the traditional working model (George et al., 2022; Ozimek, 2020). Remote workers are found to spend "10 minutes less a day being unproductive, work one more day a week, and are 47% more productive" (Bradshaw, 2024, para. 4). This increased productivity should lead to a more effective organization. The remote work style appears to be able to attract a more diverse workforce. Young mothers are still able to care for their families while building a career (Diab-Bahman & Al-Enzi, 2020). Remote work flexibility has also increased improvements in mental health, physical health, and more satisfaction with work (Chung et al., 2020).

Another ancillary benefit of telecommuting is the cost savings. For employees, there is no commuting or travel expense. For employers, there are fewer facilities and utilities to maintain as well as reduced custodial and physical security services (Silverman, 2024). It is apparent that businesses have seen the benefits that remote/hybrid working conditions are providing for their employees. Bloom (2021) found that of the companies surveyed, 70% were planning on implementing a form of hybrid/remote working conditions for their employees in the near future. Beck and Henscher (2022) conducted a study following the lockdowns in Australia. They compiled information from three waves of data: the beginning, middle, and end of the COVID-19 lockdowns. They collected data on employers that had to introduce new working conditions because of absenteeism and sickness. The survey revealed that despite the challenges of the situation, the majority of the study population wanted to keep remote working conditions in place. This was also supported by the Australian government in the form of introducing compliance and regulatory guidance for companies to favor remote/hybrid working conditions (O'Sullivan et al., 2020).

Beyond the cost savings of fewer employees onsite, employers are able to delegate tasks and manage across multiple departments and geographic limitations (Beck & Hensher, 2022). Other benefits that employers are citing from employees working from home include "increased autonomy, reduced informal communication, improved productivity, and increased job satisfaction" (Diab-Bahman & Al-Enzi, 2020, p.1).

Disadvantages for Employers and Employees

There are also disadvantages following the increase in remote/hybrid working conditions. One of the largest disadvantages is that employees report feeling socially isolated from their coworkers and from their managers. This can lead to increased stress and anxiety for employees (Van Zoonen & Sivunen, 2022). There is also a lack of consistent communication and feedback. The lack of face-to-face conversations can lead to increased confusion, less immediate feedback, and even negative emotions from employees. This feeling of dissatisfaction may not relate to the job, but to the modality of the work being done. Employees may lose enthusiasm for their jobs due to the lack of connection with other employees (Park, Fritz, & Jex, 2011). A recent survey (Chung et al, 2020) found the following reasons employees disliked working from home including "blurred boundaries between work and home, too many distractions at home, increased family stress, negative relationship with colleagues, increased workload/hours, can't work due to lack of space" (p.15).

Another concern from employers is the difficulties of managing a hybrid team. When half of the teammates are not in the office, this can create levels of mistrust and miscommunication (Giacosa et al., 2023). Managers have reported that hybrid working teams struggle to clarify their expectations because half of the team is not present when making critical decisions. Another concern from managers is that if employees are offered the chance to work remotely two days a week, the majority of them will try to extend their weekends, which could lead to a gap in the workforce and a misallocation of resources for the company. Managers are also concerned with risking a lack of diversity because of working from home initiatives (Hsu & Tambe, 2022). Bloom’s (2021) study surveyed college graduates with young families and found that women were 50% more likely to want to work from home than their male counterparts. This obvious skew of who wants to work from home and who doesn't could lead to other potential issues for employers in terms of equity and inclusion. Employees who work from home had a 50% lower rate of promotion after 21 months compared to those who had more traditional working conditions (Bloom, 2021).

An argument can also be made that hybrid/remote working conditions can be even more costly for certain employers. This is due to increased technology needs, increased training, and increased information security measures. Organizations may not have to pay for physical assets, but the long-term costs of maintaining a technology-driven workforce are increasing (Hofschulte-Beck, 2022). These disadvantages have prompted many employees to return to onsite work requirements. This creates a difficult predicament for employers who are attempting to recruit and retain talent, managing employee expectations, ensuring viability in the long-term then must toe the line between what works for certain employees and what works best for the company as a whole (Turner & Baker, 2022).

Shorter Work Week

While the concept of a four-day work week has long been discussed amongst management scholars (Fottler, 1977; Hedges, 1971; Kenny, 1974), there has been a recent surge of interest for employers to implement a shorter work week in order to address hiring and retention challenges in a post-pandemic environment (Chung, 2022; Mirella, 2020). The benefits of a shortened work week can include improved morale, increased productivity, and reduced sickness-related absenteeism (Knight, Rosa, & Mallory, 2020). Perlow and Porter (2009) found that reduced working hours can lead to more focused and efficient work. Chung (2023) describes the traditional 40-hour work week to be more about form over function. That is employees may show up for 40 hours, but the actual work being done is much less. For organizations that implement a shorter work week, due to time constraints, employees tend to prioritize essential tasks and eliminate non-essential activities, thereby enhancing overall productivity (Lewis et al., 2023).

Spicer and Lyons (2023) conducted a pilot study in Ontario where they assessed the impact of a shortened work week for local township employees. These positions included full-time staff as well as part-time employees. A pre and posttest was administered to compare and contrast the results of the employee satisfaction survey. The participants were initially surveyed in August 2020 and then post tested in October 2021. Of the multiple criteria measured, the three responses that showed a slight increase in employee satisfaction were work-life balance, enthusiasm for coming to work and working well with colleagues (Spicer & Lyons, 2023). While there wasn’t a significant difference between pre and posttest results, it should also be noted the results for negative impacts such as decreased job satisfaction, increased burnout, and fatigue were not found either.

3. METHODS

This study utilized a mixed-methods approach, collecting data from two distinct groups. The first group were business leaders and hiring managers who have previously or currently provide internships and full-time entry-level jobs to recent college graduates. The second group were college students that were planning on applying for internships or full-time employment opportunities within the next two semesters. The primary data collection tool was a pair of surveys, each tailored to the respective group, administered via SurveyMonkey.

Sample and Data Collection

The business leader/hiring manager group was identified using the resources of the local university’s Career Service Center. This group received an email invitation containing a link to the survey, which was designed specifically for employers. The prospective employee (student) group was targeted through a presentation that included a QR code linking to their survey. These students, within one year of graduating from the Business School of the same local university in northeast Ohio.

Survey Design

The survey for business leaders consisted of 24 questions, including demographic inquiries

(Questions 1-3), assessments of hybrid versus remote working conditions (Questions 4-14), evaluations of a shortened workweek (Questions 15-18), and queries regarding employee wellness programs (Questions 19-22). The student survey mirrored the business leader survey but was adjusted to focus on the perspectives of individuals entering the workforce.

Both surveys were informed by previous research conducted in the wake of the COVID-19 pandemic, with employer and employee questions adapted from similar studies (Boland et al., 2020; Lipman, 2021; Chung et al., 2021; Laker, 2022).

We sent out survey requests to 40 prospective employers. The number of total respondents for employers was (n=34). We sent out over 100 invitations to upper-class students within the School of Business and received a total number of 40 responses.

Study Population	Sample Size:
Employer	n = 34
Student (prospective employee)	n = 40

Table 1: Study Population

4. RESULTS

Hypothesis 1: *The majority of the businesses surveyed will see the benefits of remote/hybrid working conditions.*

The following are survey questions (questions #5, 7, 10, and 12) that relate to the benefits of remote and/or hybrid working conditions and the data results and pie charts.

Question #5: Select all that apply: Potential positives that I foresee if the organization that I represent offered remote working conditions to their employees include.

Interval	Frequ ency	Relative Frequency	Percent Frequency
Increased productivity	14	0.222	22%
Increased work satisfaction	25	0.396	40%
Increased company loyalty	13	0.206	21%
None of the Above	3	0.047	5%
Other	8	0.126	13%
Total	63	1	100%

Table 2: Frequency Table for Question #5

Most of the business leaders who participated in this survey responded that an increase in work satisfaction and productivity are the two most impactful benefits of offering remote working conditions to their employees.

The pie chart below is a graphical representation of Table 2.

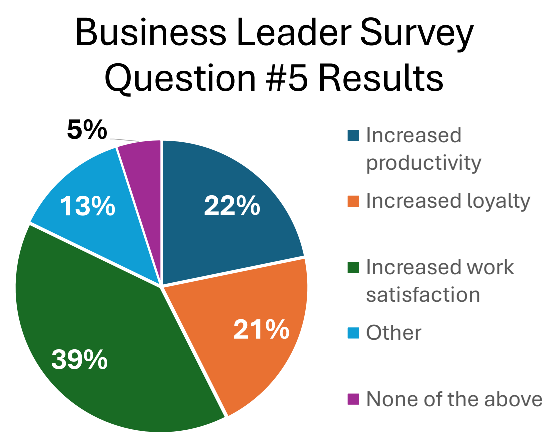

Figure 1: Business Leader Survey Question #5 Percent Frequency

Question #7: Rate your level of agreement with the following statement: As an employer, I see the benefits of remote working conditions.

A floating scale was utilized for this question. The respondents' selections were not discreet. They could range anywhere from 1-5 including intervals in between them. For the purposes of reporting the results, the data was standardized from 0 to 100, and so when reviewing the results can be evaluated from 0 to 100.

Interval	Frequ ency	Relative Frequency	Percent Frequency
0-10	5	0.147	15%
11-20	1	0.029	3%
21-30	1	0.029	3%
31-40	1	0.029	3%
41-50	4	0.117	12%
51-60	2	0.058	6%
61-70	1	0.029	3%
71-80	7	0.205	21%
81-90	3	0.088	9%
91-100	9	0.264	26%
Total	34	1	100%

Table 3: Frequency Table for Question #7

Most of the business leaders' survey responses show a slight benefit to fully remote working conditions. The top three responses ranged from 91-100 (26%), 71-80 (21%), and 0-10 (15%). The overall mean was 63.47. On a standardized scale, this results in an average of 3.17. The mean falls within the "Agree" category. A majority of hiring managers either agree or strongly agree they can see the benefits of a remote work environment.

The pie chart below is a graphical representation of Table 3.

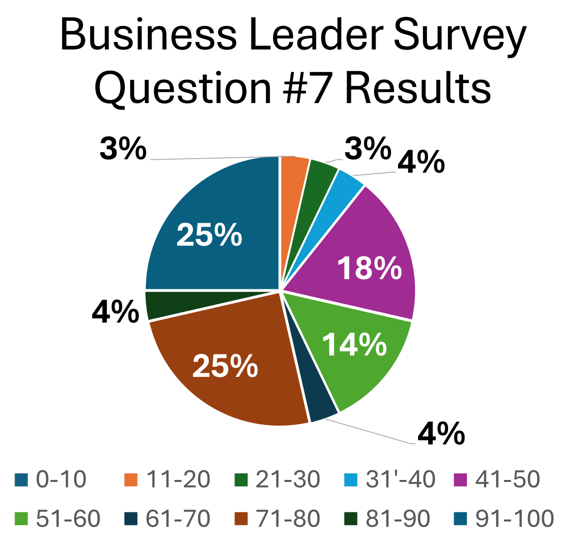

Figure 2: Business Leader Survey Question #7 Percent Frequency

Question #10: Select all that apply: Potential positives that I foresee if the organization that I represent offered hybrid working conditions to their employees include:

Interval	Frequency	Relative Frequency	Percent Frequency
Increased productivity	21	0.272	27%
Increased work satisfaction	26	0.337	34%
Increased company loyalty	19	0.246	25%
None of the Above	2	0.025	3%
Other	9	0.116	12%
Total	77	1	100%

Table 4: Frequency Table for Question #10

Respondents were able to choose multiple responses to this question. The majority of hiring manager responses recognize the benefits of a hybrid work environment, including the potential for increased productivity, work satisfaction, and loyalty.

The pie chart below is a graphical representation of Table 4.

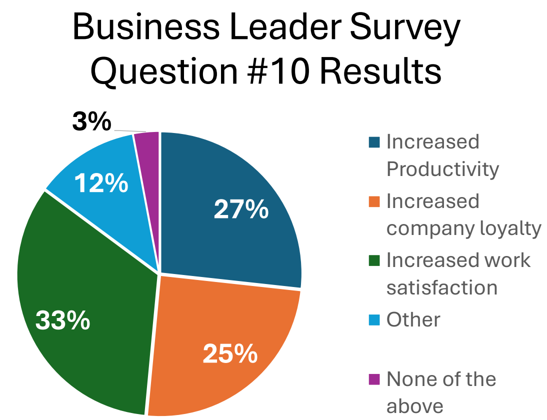

Figure 3: Business Leader Survey Question #10 Percent Frequency

Question #12: Rate your level of agreement with the following statement: As an employer, I see the benefits of hybrid working conditions.

A floating scale was utilized for this question. The respondents' selections were not discreet. They could range anywhere from 1-5 including intervals in between them. For the purposes of reporting the results, the data was standardized from 0 to 100, and so when reviewing the results can then be evaluated from 0 to 100.

Interval	Frequency	Relative Frequency	Percent Frequency
0-10	6	0.176	18%
11-20	2	0.058	6%
21-30	0	0	0%
31-40	0	0	0%
41-50	3	0.088	9%
51-60	0	0	0%
61-70	4	0.117	12%
71-80	1	0.029	3%
81-90	1	0.029	3%
91-100	17	0.5	50%
Total	34	1	100%

Table 5: Frequency Table for Question #12

Many of the business leaders who participated in the survey recognized the benefits of utilizing a hybrid working environment. The highest response fell within the 91-100 interval range (representing 50 % of the responses). The overall mean was 68.88. On a standardized scale, this results in an average of 3.44. The mean falls within the "Agree" category. A majority of hiring managers strongly agree they can see the benefits of a hybrid work environment.

The pie chart below is a graphical representation of Table 5.

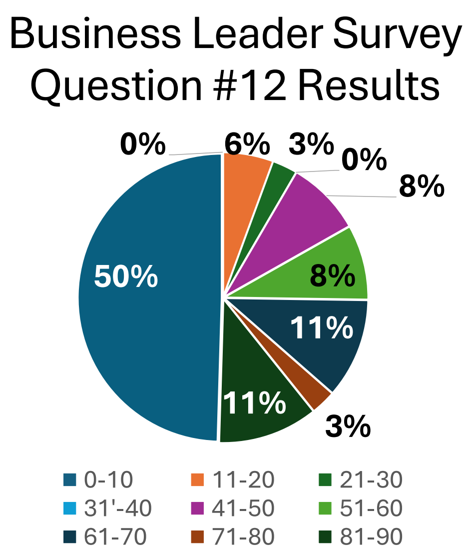

Figure 4: Business Leader Survey Question #12 Percent Frequency

Hypothesis 1 Results

The information collected from question #5 reveals that work satisfaction and increased productivity are the most important potential positives that employers anticipate from implementing a fully remote work option. This is supported by the results of question #7, which shows that employers can see the benefits of fully remote working conditions. Question #10 reveals that work satisfaction, work productivity, and increased company loyalty are all potential positives that employers anticipate coming out of offering hybrid working conditions. The responses from question #12 demonstrate that a majority of the employers surveyed see the benefits of offering hybrid working conditions.

Hypothesis 2: A majority of the businesses surveyed will see the benefits of a shortened work week and be willing to move employees to a shortened work week.

The following are survey questions (questions #16 and #15) that relate to employers' willingness to implement a shortened work week and the data results and pie charts.

Question #16: Select all that apply: A shortened workweek would be beneficial to my organization.

Respondents were free to choose as many of these variables as they deemed appropriate for the select all that applies questions.

Intervals	Frequency	Relative Frequency	Percent Frequency
None of the Above	8	0.125	13%
The employees would be more productive	9	0.140	14%
More people would apply to work at the organization (an increased talent pool to choose from)	16	0.25	25%
The employees would be less stressed at work	11	0.171	17%
The employees would experience high satisfaction levels	19	0.296	30%
Other	1	0.015	2%
Total	64	1	100%

Table 6: Frequency Table for Question #16

The responses in Table 6 suggest that a majority of business leaders see the benefits of a shortened work week, which include higher satisfaction levels, more applications, and less stress.

The pie chart below is a graphical representation of Table 6.

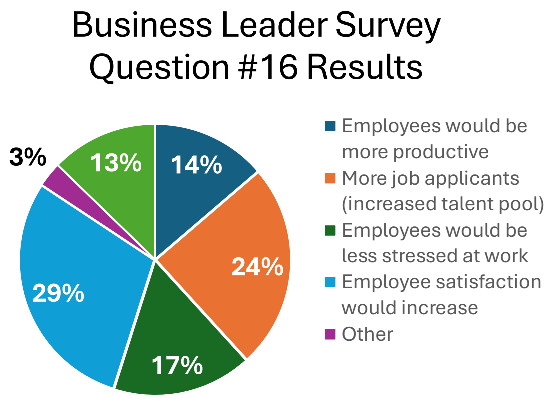

Figure 5: Business Leader Survey Question #16 Percent Frequency

Question #15: Rate your level of agreement with this statement: The organization I represent would be open to offering my employees a shortened workweek (4 days) in the future.

A floating scale was utilized for this question. The respondents' selections were not discreet. They could range anywhere from 1-5 including intervals in between them. For the purposes of reporting the results, the data was standardized from 0 to 100, and so when reviewing the results can then be evaluated from 0 to 100.

Interval	Frequency	Relative Frequency	Percent Frequency
0-10	15	0.441	44%
11-20	2	0.058	6%
21-30	3	0.088	9%
31-40	0	0	0%
41-50	6	0.176	18%
51-60	1	0.029	3%
61-70	4	0.117	12%
71-80	2	0.058	6%
81-90	0	0	0%
91-100	1	0.029	3%
Total	34	1	100%

Table 7: Frequency Table for Question #15

Many of the business leaders who participated in the survey recognize the benefits of introducing a shortened work week, but an overwhelming majority are unlikely to implement this strategy. The highest response fell within the 0-10 interval range (representing 44 % of the responses). The overall mean was 30.26. On a standardized scale, this results in an average of 1.51. The mean falls within the "Disagree" category. A majority of hiring managers strongly disagree that their organization would be willing to implement a shortened work week.

The pie chart below is a graphical representation of Table 7.

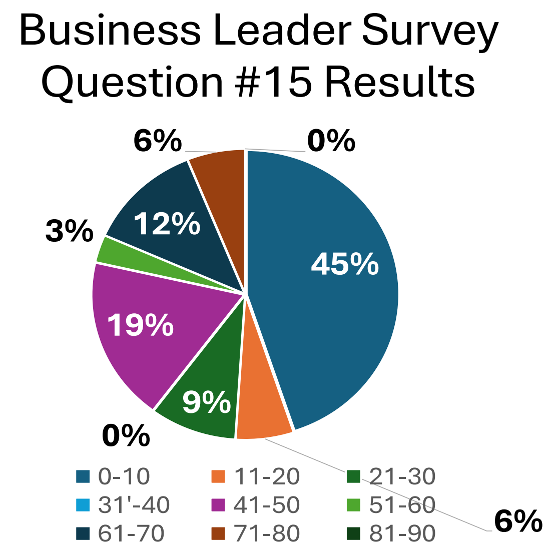

Figure 6: Business Leader Survey Question #15 Percent Frequency

Hypothesis 2 Results

The information collected from question #16 reveals that a shortened work week is a viable option to recruit and retain new and existing talent. However, the results of question #15 reveal a disconnect between the benefits of a shortened work week and the likelihood of implementing this benefit. Employers were unlikely to introduce this as an option at the time of this study.

5. DISCUSSION

The results of this pilot study may provide valuable insights into what the future of the work environment post COVID-19. Both employers and employees were introduced to remote/hybrid working conditions due to government mandates and business contingency plans. This new working environment has many advantages and disadvantages to all parties. Employees were not able to enjoy the flexibility of managing their commute, work hours, and physical meetings. The freedom to work from home provided opportunities for employees to get more work done in less time. The disadvantages that employees experienced included reduced working relationships, social isolation, and potential increased workload.

Even though the majority of employees have a favorable opinion towards adopting remote/hybrid working conditions, employers are not as certain about this change. Interestingly, the results of this study indicate that employers clearly recognize the benefits of a remote/hybrid work environment. The responses show that employees may feel increased work satisfaction, increased productivity, and a stronger sense of company loyalty if remote/hybrid working conditions were employed. This does not necessarily mean that companies are jumping to change their current working format. The data suggests that employers are only slightly willing to consider moving employees who currently work in person to hybrid working conditions and are not willing at all to consider moving employees who currently work in person to remote working conditions. Employers often cite the additional challenges of increased communication tools, cyber security risks, the potential for discrimination, and a lack of diversity and creativity among homogenous groups. Overall, employers seem to be more willing to entertain the idea of allowing their employees to work in hybrid conditions, but they are not racing to adopt a new system that may introduce new challenges and uncertainty.

Additionally, while employers also see the potential benefits of a shortened work week, the overwhelming majority of the respondents stated they would not be likely to introduce a four-day work week at this time. Part of the challenge may be the respondents representing the employers are mostly HR staff and hiring managers. This may not be within their realm of responsibility or scope of authority.

6. CONCLUSION

This research project is important when examining the working expectations of future employees and what current/future employers are willing to provide for them in the near future. The limitations facing this study included sample size limitations and the overall scope of discussions. One of the surveys created was sent to a local university's business students and the other survey was sent to full-time job and internship providers for the Career Services department of the same local university. This could make the survey hard to replicate. If this survey were to be replicated on a larger scale with multiple different universities and colleges and surrounding employers, the sample size limitations would be reduced. The data that was presented may help to provide insights into the tension unfolding between employees who want a remote/hybrid workplace with shortened work weeks and employers who are hesitant to provide these benefits. Future studies may focus on the specific challenges that employers are facing as they try to implement these organizational strategies.

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