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ABSTRACTS

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Large Language Models for Phishing and Spam Detection: A BERT Approach

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ABSTRACT

In the modern world, emerging hazards not only attack computers but also steal personal information and financial resources. The most widely used means of interaction lately are emails and text messages, and as the percentage of emails increases, so does the amount of spam and phishing. Spam is any type of unwanted, unauthorized electronic communication that is transmitted in large quantities. Spam emails and instant messages waste a lot of resources by redundantly inundating wireless networks. However, most spam emails are sent by commercials looking to promote their offerings, and few are extremely malicious in nature, such as phishing emails, which attempt to trick those targeted into disclosing confidential data such as website credentials or credit card details. Phishing offers a combination of technological and social engineering techniques to steal data on victims' identities and accounts, it is imperative to curtail the threat and criminal activities associated with it. Spam and Phishing mail have become increasingly prevalent significantly in recent years, necessitating sophisticated countermeasures. Despite developed approaches for detecting this type of email, a comprehensive solution remains needed to combat these threats. Mail detectors will be used to identify spam, phishing, and ham messages. This research focuses on demonstrating the potential of a Large Language model technique (specifically the pre-trained BERT model) to detect phishing and spam emails according to their context. A comparative evaluation and analysis are conducted on these approaches. The performance of the model is measured using various evaluation metrics such as Accuracy, Precision, Recall, and F1-Score.

INTRODUCTION

The advent of the internet, the E-Mail acronym for electronic mail has become an essential method of communication used in nearly every area of life. Communication through email is one of the most important tools in nearly every field, from businesses to corporations to education institutions to individual users. It has become more common in recent years to carry out cyber-attacks using social engineering techniques using spam and phishing emails. Despite constant updates of security protections, people are being convinced to provide sensitive information, account IDs, passwords, and bank details. Instant messages, Emails, and phone calls are widely used to launch such cyber-attacks. Most of the email traffic is either spam or phishing which causes severe damage, malware infections, ransomware attacks, account compromise, and data loss. Therefore, developing comprehensive solutions for digitized identification and prevention of these dangerous emails has grown into a top priority. Conventional methods for detecting spam and phishing emails rely on rule-based systems, content-based filters, and machine-learning algorithms. However, these approaches have limitations due to their reliance on handmade indicators and established standards, which may not capture complex details and contexts associated with fraudulent emails.

Recent developments in Natural language processing (NLP) and machine learning have enabled large language models like BERT to solve text-related tasks, enhancing context awareness, grammatical linkages, and accurate depictions from text input. For the research, a custom dataset labeled spam, ham, and phishing emails, we will fine-tune the BERT model after preprocessing the data to eliminate noise and redundant details. The effectiveness of the BERT model will be assessed using a variety of evaluation metrics including accuracy, precision, recall, and F1-score.

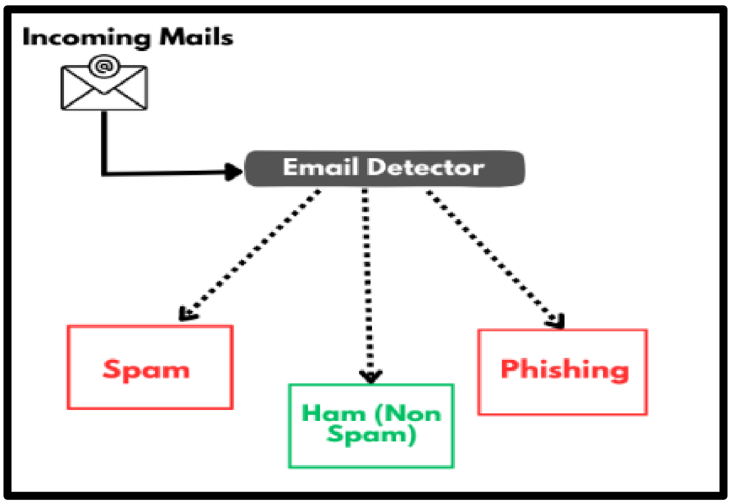
This research study aims to improve the privacy and dependability of electronic mail by successfully recognizing and filtering fraudulent emails. Its findings may aid in designing better filtering frameworks and reducing spam and phishing risks for individuals and enterprises. The structure of the paper is designed as follows: In section 2, we will provide a background into some issues of spam and phishing emails and their financial consequences, and in section 3 we will discuss related works. Section 4 describes our methodology framework using a fine-tuned BERT model for phishing and spam email detection. The experimental results are discussed in Section 5. Finally, conclusion of our findings and future work in section 6.

BACKGROUND

Spam mail, also known as unsolicited bulk emails, are messages that are distributed widely and frequently in large quantities to a wide range of recipients. It often contains cryptic messages, scam activities, or phishing content. Spam emails, which are frequently sent without the recipient's permission, frequently contain commercial content as well as promotions, scams, malware, illegal activities, and personal information. David, E. S. (2001) stated advertising messages account for 36% of all spam messages and they might be perceived as disrespectful or irritating. Adult-related content makes up 31.7% of spam communication, while financial issues make up 26.5%. Scams and fraudulent accounts account for 2.5% of spam emails, with 73% of phishing scams primarily aimed at identity theft. One out of every 12,500,000 spam emails get a response. Phishing emails that frequently imitate the logo or style of acclaimed companies are internet scams that coerce users into giving confidential data. These emails frequently include links to fake internet pages or solicit personalized submissions. A recipient may suffer monetary losses because of receiving phishing emails, which have been engineered to appear legitimate (Sahmoud et al., 2022).

Phishing email detection increased from 1,097,811 in Q2 and 1,025,968 in Q1 to 1,270,883 in Q3 2022, according to the Anti-Phishing Working Group (APWG). Phishing attacks go beyond the theft of personal information; the APWG covers many instances in which hackers gain private information like login passwords without permission (APWG, 2022). Fig 1 shows a mail detector that detects unsolicited, unwanted, and virus-infected emails, preventing them from reaching users' inboxes. Email detectors use techniques like block-list filtering to separate spam and phishing emails based on the sender.

Fig 1: Email Detector



However, this method is ineffective for identifying fraudulent users as it only works after the latest spam or phishing email has been added to the block-list. Rule-based and signature-based email filtering have been shown to be ineffective against evolving spam and phishing tactics. Instantaneous spam and phishing email recognition requires sophisticated detection systems. The study employs contextual language understanding, classification of text, extracting features, and email comparison analysis to detect spam and phishing emails using a pre-trained BERT (Bidirectional Encoder Representations from Transformers) model from natural language processing. A pre-trained language model called BERT can recognize the intricacies of natural language by comprehending the underlying relationships between words and phrases. It was created by Google AI in 2018 and it is used to employ tasks requiring natural language conceptualization. Shanmugasundaram et al., (2017) stated in BERT, a model is trained for a general task and fine-tuned for a new one. It has been trained in two tasks: masked language prediction and prediction of sentences. It uses a transformer model encoder that tokenizes every word in a sentence and provides each tokenized word with a vector representation.

PROBLEM STATEMENT

Insufficient study has been done on the best adaptation and fine-tuning for email filtering, taking characteristics and difficulties into account, leaving BERT's efficiency in identifying spam and phishing emails unproven. According to data (Vaswani, et al.,2017), 52% of the respondents said that spam was a big challenge, making spam a significant concern for nearly all internet users. The FBI's Internet Client Complaint Center "IC3" claimed a loss of 12.5 billion USD to commercial email users. Approximately 90% of all cyberattacks begin with phishing emails, according to recent statistics. They represent a large portion of all email-based threats (Vergelis, et al., 2019). Kaspersky Labs claims Spam accounted up, on average, 45.56% of all email traffic in 2021. Phishing attacks result in billions of dollars in financial losses each year, according to research. According to Widup, et al., (2019) and Verizon's 2019 Data Breach Investigations Index (DBIR), the overall global loss for the period between June 2016 and December 2021 highlighted 43 billion USD. As phishing and spam attacks become more sophisticated and convincing, they become harder to detect and defend against, which poses a significant risk to data security and privacy.

Based on the specific requirements and complexities of email filtering, how can BERT be used effectively for spam and phishing detection particularly in terms of scalability, accuracy, and efficiency? The statistics on spam and phishing emails will help us use BERT, an NLP model, to create an effective email detection model that performs better at recognizing these emails. To enhance BERT's effectiveness at identifying spam and phishing emails, new approaches are being explored in terms of feature representation, training methods, model architecture, and dataset augmentation.

RELATED WORKS

Numerous studies explore developing efficient email detectors, researchers have created spam and phishing detection systems utilizing combine-based, deep learning, and machine learning techniques. Deep learning needs enormous amounts of data to perform better than machine learning, which is best with modest amounts of data. Real-world issues like picture categorization and word processing implement both methodologies.

According to (Tong, et al., 2021) a long-short attention mechanism was used to create a Chinese spam detection model that turned words into vectors based on the context of the phrase. The model has a 99.3% accuracy rate after being trained using Trec06C. Anggrainingsih et al., (2022) demonstrates that the accuracy of detecting misinformation is improved using a neural network and a BERT-based fine-tuned language model. On both short- and long-text datasets, the suggested models beat the most recent state-of-the-art models. On the Pheme1 R/NR dataset, experimental findings demonstrate that refined RoBERTa LM models achieve 88.9% accuracy in separating rumor and non-rumor tweets, outperforming state-of-the-art approaches. Choudhari & Das (2021) suggest a blockchain-based architecture to stop hackers and spammers from sending out spam and phishing emails. The framework links an email address to a wallet account in exchange for an ETH processing charge. The costs are returned to the sender's wallet if genuine emails are sent. This imposes a limitation for fraudulent users to prevent utilizing the same mechanism.

Labonne & Moran (2023) shows that Local Machine Learning (LLMs), particularly in few-shot circumstances, is successful at detecting email spam. Across all training sample sizes, LLMs outperform baseline approaches in terms of F1 score. The solution Spam-T5, which has an average F1 score of 0.7498, performs the best overall. This shows that LLMs can be useful tools for dealing with spam detection issues without making significant data identification efforts. Tida & Hsu (2022) incorporated linear layers, dropout layers, batch normalization layers, ReLU activations, and log softmax activations, the researchers refined a pre-trained model. Hyper-parameter adjustment was used to create the final model, with batch size 128 providing the best fit for models trained on five datasets. With an accuracy of 97% and an F1-score of 0.96, the merged dataset performed well by detecting spam mails using Transfer Learning of BERT Model. According to Raffel et al., (2020) the use of datasets from various tasks, the Flan-T5 method for improving model fine-tuning achieves notable improvements on common natural language comprehension tasks. To demonstrate their potential for enhancing natural language comprehension, this research compares Flan-T5 against traditional models for email spam detection.

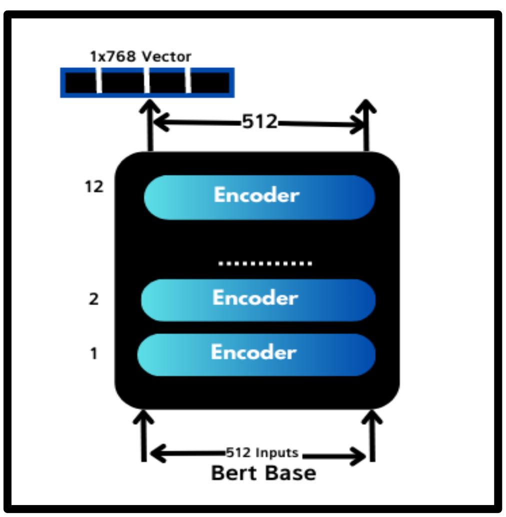
Harisinghaney et al., (2014) optimized the detection of spam email using KNN, Naive Bayes, and reverseDBSCAN, and improved precision score between 2 and 6% by using Word Sense Disambiguation preprocessing on Ling Spam and TREC datasets. Tida & Hsu, (2022) employed fine-tune BERT for spam detection. They used a variety of datasets to train and test the model. The model's performance for each dataset was as follows: The Enron dataset, the Ling- Spam dataset, the Spam Text dataset, and the SpamAssassin dataset all earned f1 scores of 94%,96% and 97% respectively. With the use of the TF-IDF and NB method, Jánez-Martino et al. (2020) combined model of TF-IDF and SVM demonstrated 95.39% F1 Score and the quickest spam categorization. With an accuracy and F1 score of 81.6% and 76.6%, respectively, Vazhayil et al. (2018) research combined ML techniques including Random Forest, Decision Trees, Logistic Regression, and Support Vector Machine (SVM) for phishing email identification achieved a strong classification rate. This approach eliminates the requirement for manual blacklisting and expertise by relying on feature engineering to construct tasks and present emails.

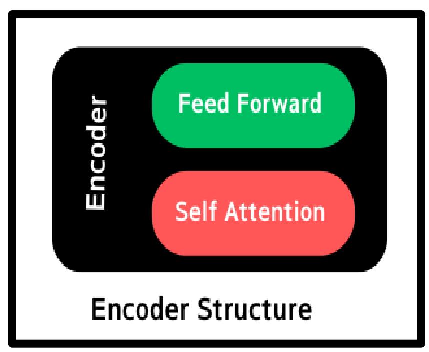
Passive warnings were unsuccessful, according to Egelman, et al., (2008) as only 13% of participants paid attention to them. Most toolbars adopted passive warnings, which prevented them from appropriately alerting end users to the dangers of phishing. Users did not pay attention to toolbar passive warnings, according to Min Wu et al., (2006) the findings of both research, active warnings are preferable than passive ones since users will not take notice of a warning unless something is done to push them to, such as preventing access to content-data portions of the user interface (UI). According to Marie-Sainte & Alalyani, (2020) for spam identification, Faris offered a PSO-based Wrapper with Random Forest algorithm and Marie-Saint provided Deep Learning-based methods. The suggested approach outperformed SVM by itself in the analysis of Arabic text.

METHODOLOGY

The approach identifies three classes of emails: phishing emails, Spam and Ham (good emails). A collection of features has been identified as particularly successful in detecting phishing, and as attacks evolve, new features will need to be identified. In BERT, there are two types of encoders: BERT large and BERT base. With BERT base, you'll find 12 encoders from the Transformer model with hidden sizes of 768 and 1024, and with BERT large, you'll find 24 encoders with hidden sizes of 1024 and 768. Using transformer encoders, words are encoded based on sentence context by the self-attention layer and their output is processed to fit the input of the next attention layer. The feed forward neural network layer processes the output to fit input for the next attention layer. Fig 2 shows the Bert base architecture. This NLP model's transformer architecture and bidirectional analysis improve its accuracy for naming entity recognition and segmentation of speech. It is essential for many NLP applications since it is particularly good at comprehending text context.

Fig 2: Bert Base Architecture





BERT is a powerful natural language processing tool that has been trained on a 3-billion-word dataset and excels in NLP tasks like sentiment analysis, language translation, and answering questions. An email detector is created by fine-tuning the BERT base by adding a fully connected classifier layer over the pre-trained model. This process is called fine-tuning the BERT model because the output is fed to a single fully connected layer that makes binary classifications, determining whether a message is spam, phishing, or ham (non-spam).

The pipeline overview for the email detection follows these procedures:

- **Data Loading**: We loaded a custom dataset from a CSV file, including ham (non-spam), spam, phishing categories with corresponding emails.

- **Exploratory Data Analysis (EDA):** We conducted some EDA to acquire an overview of the statistics in the data.

- **Data Pre-Processing:** To make the data model compatible, we conducted some preprocessing based on the results of the EDA.

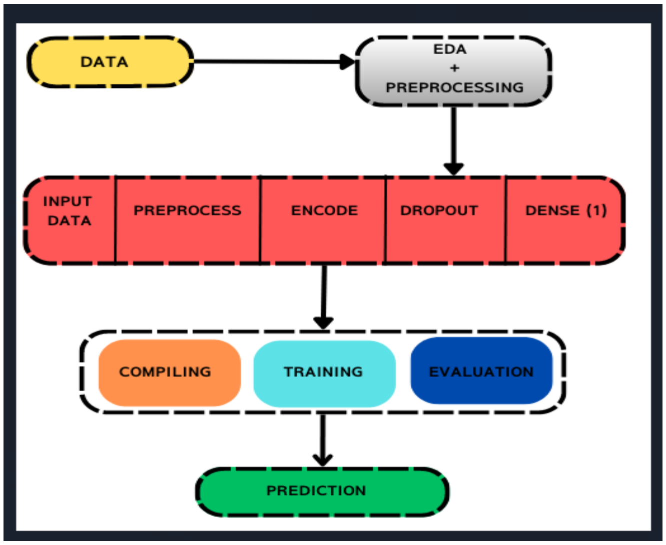
- **Model Development:** Using the Functional API*, a model using deep learning will be created that consists of an input layer, a Bert preprocessor (which adds mask and encodings), a Bert encoder, a Bert embedder, a dropout layer to mitigate overfitting, and a softmax layer to forecast data in two classifications. The model will perform two more general stages in addition to producing contextualized word embedding for training data.

- **Model Evaluation:** Based on the results, several relevant statistics and metrics will be presented once the model has been assessed using the test data.

- **Predicting Data:** Finally, we will use the model for predicting our personalized emails.

Fig 3 illustrates the logic's general flow.

Fig 3: Email Detection Pipeline Logic Flow



HARDWARE AND ENVIRONMENT SETTING

The experiment presented in this paper was conducted using a Dell Inspiron 14 mounted with the 64-bit operating system, x64-based processor and the processor is 12th Gen Intel(R) Core (TM) i7-1255U 1.70 GHz. The models were built, trained, evaluated, and tested using the Google Collaboratory with a runtime type -Python 3, hardware accelerator -GPU and a T4 GPU type. We imported a few python libraries including TensorFlow hub Place-where all TensorFlow pre-trained models are stored, TensorFlow-for model creation, TensorFlow text-allows additional NLP text processing capabilities outside the scope of TensorFlow. Pandas- for data loading, manipulation, and wrangling. Sklearn-for data splitting. Matplotlib-for visualization support.

DATASET

This study used a custom generated dataset. The dataset contains 5761 instances, the majority of which are messages and are related to the category of spam, phishing, and ham. A sample of the data set is shown in Fig. 4.

Fig 4. Sample of Custom Email Dataset

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	ham	U dun say so early hor... U c already then say...
3	ham	Nah I dont think he goes to usf, he lives arou...
4	ham	Even my brother is not like to speak with me. ...
...	...	...
5756	phishing	2 new message
5757	phishing	your bill is here
5758	phishing	please check your
5759	phishing	email has been reposted , regulation
5760	phishing	request to deactivate

5761 rows × 2 columns

It was discovered that the custom dataset had approximately (4825 non-spam emails, 747 spam emails, and 189 emails that were phishing attempts. The category count is shown below in Fig. 5.

Fig 5. Category count of Custom Email Dataset

```
df['Category'].value_counts()

ham         4825
spam         747
phishing     189
Name: Category, dtype: int64
```

TRAINING THE MODEL

The dataset is then loaded into BERT to generate a contextualized embedding vector of length 768. BERT was used in detecting emails and comparison was done among the 3email categories. We will first apply preprocessing using the preprocessor object and then pass this preprocessed text to our model to generate the contextualized embedding vector. After that, we then pass this embedding vector to a single neuron in output to do binary classification. The category of the dataset clearly shows that the dataset is imbalanced and there is a need for regularization. For maximizing performance, we carried out a dataset down sampling to check the percentage of unbalanced and created a new data frame out of the existing one. Down sampling is a technique where the dominant class is reduced in size to match the minority class.

For the dataset comparison using Ham and Spam- the percentage of the unbalanced dataset was 15% and the random minority no of sample- (747) for majority class (4825). For the Phishing and Spam comparison category-the percentage of the unbalanced dataset was 25% and the random minority no of sample- (189) for majority class (747). The Phishing and Ham comparison category-the percentage of the unbalanced dataset was 4% and the random minority no of sample- (189) for majority class (4825). We created a balanced dataset by condensing 2 new data frames for each of the category comparisons as shown in Fig 6, 7 and 8.

Fig 6. Balanced Ham and Spam Custom Dataset

```
# concating both dataset - df_spam and df_ham_balanced to create df_balanced dataset
df_balanced = pd.concat([df_spam , df_ham_downsampled])
df_balanced.head()
```

	Category	Message
4825	spam	Free entry in 2 a wkly comp to win FA Cup fina...
4826	spam	FreeMsg Hey there darling its been 3 weeks now...
4827	spam	WINNER As a valued network customer you have b...
4828	spam	Had your mobile 11 months or more? U R entitle...
4829	spam	SIX chances to win CASH From 100 to 20,000 pou...

```
df_balanced['Category'].value_counts()
```

```
spam    747
ham     747
Name: Category, dtype: int64
```

Fig 7. Balanced Spam and Phishing Custom Dataset

```
# concating both dataset - df_phishing and df_spam_balanced to create df_balanced dataset
df_balanced = pd.concat([df_phishing , df_spam_downsampled])
df_balanced.head()
```

	Category	Message
5572	phishing	Are you available ?\nNo calls text only 951307...
5573	phishing	Im in a meeting and need help getting some Ama...
5574	phishing	Hello RECIPIENT\n\nI am urgently seeking for a...
5575	phishing	Are you around? I need to pay a vendor with th...
5576	phishing	Im in a meeting and need help getting some Ama...

```
df_balanced['Category'].value_counts()
```

```
phishing    189
spam        189
Name: Category, dtype: int64
```

Fig 8. Balanced Ham and Phishing Custom Dataset

```
# concating both dataset - df_phishing  and df_ham_balanced to create df_balanced dataset
df_balanced = pd.concat([df_phishing , df_ham_downsampled])
df_balanced.head()
```

	Category	Message
5572	phishing	Are you available ?\nNo calls text only 951307...
5573	phishing	Im in a meeting and need help getting some Ama...
5574	phishing	Hello RECIPIENT\n\nI am urgently seeking for a...
5575	phishing	Are you around? I need to pay a vendor with th...
5576	phishing	Im in a meeting and need help getting some Ama...

```
df_balanced['Category'].value_counts()
```

```
phishing    189
ham         189
Name: Category, dtype: int64
```

In the data preparation, we created a numerical representation of category using One hot encoding and applying the Lambda Function - if spam return 1, else return 0 (for ham (non-spam) - ternary operators: [lambda x: value expression else value] and this was done for each category comparison. Data processing may be used to feed a model, which, when put to the test, might discover patterns, and forecast outcomes with accuracy. A significant portion of the population undergoes training using data that makes up 80% of the input, including messages and categories. The model does not use the remaining 20%. Without biases, evaluation can forecast how the 20% will do. We carried out the train-test split on each comparison set by splitting the dataset into 80-20 ratio with 80% train and remaining as test. For evenness of data, we used to stratify an argument which ensures the same ratio of both categories is loaded for each case, even if one category has more training samples this prevents overfitting.

Our Model BERT is used for preprocessing our training data that will be fed - includes **adding additional to). This, PAD and SEP** to generate `input mask`, `input_type_ids`, `input_word_ids (token given to each word in sentences). This model has 2 parts: - Bert preprocessor - preprocess the text to be BERT ready- Bert encoder - do the actual encoding (main model (layers – 12, Hidden Layers – 768 and Attention – 12). For the Preprocessor we created a keras hub layer from the preprocessing url and for the encoder we created a keras hub layer from the encoder/ model url. The summary of the model is shown in fig 9.

Fig 9. Model Summary

```
# check summary of model
model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 Inputs (InputLayer)            [(None,)]            0           []

 keras_layer (KerasLayer)       {'input_word_ids':   0           ['Inputs[0][0]']
                                (None, 128),
                                 'input_mask': (Non
                                e, 128),
                                 'input_type_ids':
                                (None, 128)}

 keras_layer_1 (KerasLayer)     {'sequence_output':  109482241   ['keras_layer[0][0]',
                                 (None, 128, 768),                'keras_layer[0][1]',
                                 'pooled_output': (               'keras_layer[0][2]']
                                None, 768),
                                 'encoder_outputs':
                                 [(None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768),
                                 (None, 128, 768)],
                                 'default': (None,
                                768)}

 Dropout (Dropout)              (None, 768)          0           ['keras_layer_1[0][13]']

 Dense (Dense)                  (None, 1)            769         ['Dropout[0][0]']

==================================================================================================
Total params: 109,483,010
Trainable params: 769
Non-trainable params: 109,482,241
__________________________________________________________________________________________________
```

The model summary returns the model architecture and none of the trainable and non-trainable parameters (weights), as can be seen, there are over 109,483,010 parameters that are from the BERT model itself and are non-trainable.

EVALUATION AND PERFORMANCE METRICS

There are several metrics that are considered when evaluating the performance of model trained on the custom dataset. For each class, the model calculates the confusion matrix and the F1-score based on the ham/spam/phishing categories comparison. However, “spam” classes are categorized as true positives, false positives, or false negatives, based on the input label. True negatives indicate the input label is ham. The true positive value of the "Ham" class indicates the total number of inputs classified as spam but classified as ham. Finally, true negative indicates the total number of inputs labeled as spam and predicted as spam, whereas false positive represents the total number of inputs incorrectly classified as spam but labeled as ham. Three metrics are computed for each class using a confusion matrix:

1. Recall: which represents the proportion of properly recognized objects.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

2. Precision: which represents the fraction of things that were detected positively.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

3. F1-score: the f1-score, which is determined using an equation, is a weighted harmonic mean of accuracy and recall that assesses how well the model performed.

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision + Recall}}$$

4. Accuracy: is the percentage of correctly classified data that is a true positive or true negative.

$$\text{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{True Positive + True Negative False Positive +False Negative}}$$

EXPERIMENTAL RESULTS

The fundamental process in the model building process involves compilation processes utilizing binary cross-entropy as a loss function and Adam as an optimizer, using metrics such as accuracy, precession, recall, and loss. Training was done by fitting the model with the training set and running it with 10 training epochs that mean the whole dataset are used to train the model for 10 times. For the evaluation of performance, experimental work conducted in this research improved test accuracy by reducing the imbalance dataset of category in the number of records in the dataset. Our results after training the model using the training datasets and model evaluate for each category are as follows:

HAM AND SPAM EMAIL CATEGORY RESULT

We train our model and split it into 80 % for training dataset and 20% for evaluation, figure 10 shows the confusion matrix and we can see that our spam detector model detects 154 emails correctly as ham (0) and classifies 168 emails correctly as spam (1). The accuracy of the model is 86%. However, Table 1 shows the “Recall”, “Precision”, and “F1-scores” for Ham and Spam category model performance.

Fig 10. Confusion Matrix for Ham and Spam Custom Dataset

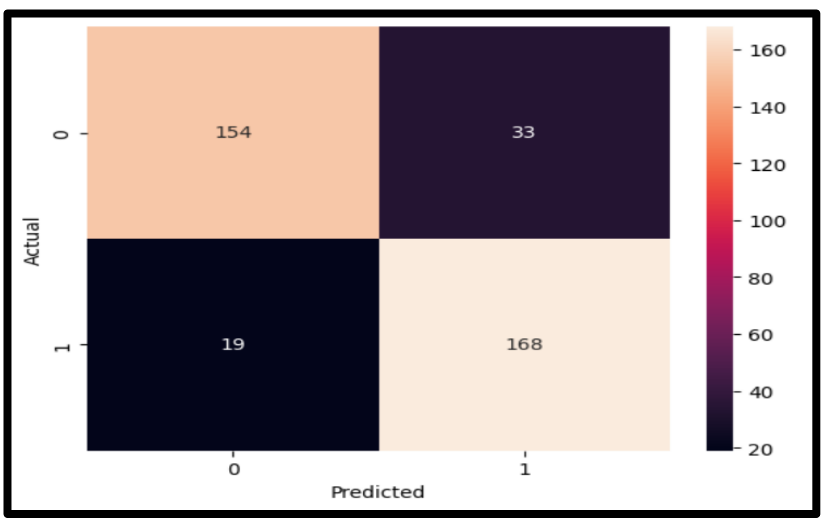


Table 1: Classification Report for Ham and Spam Category

```
# printing classification report
print(classification_report(y_test , y_pred))
```

	precision	recall	f1-score	support
0	0.89	0.82	0.86	187
1	0.84	0.90	0.87	187
accuracy			0.86	374
macro avg	0.86	0.86	0.86	374
weighted avg	0.86	0.86	0.86	374

SPAM AND PHISHING EMAIL CATEGORY RESULT

We train our model and split it into 80 % for training dataset and 20% for evaluation, figure 11 shows the confusion matrix and we can see that our spam detector model detects 42 emails correctly as spam (0) and classifies 38 emails correctly as phishing (1). The accuracy of the model is 84%. However, Table 2 shows the "Recall", "Precision", and "F1-scores" for Ham and Spam category model performance.

Fig 11. Confusion Matrix for Spam and Phishing Custom Dataset

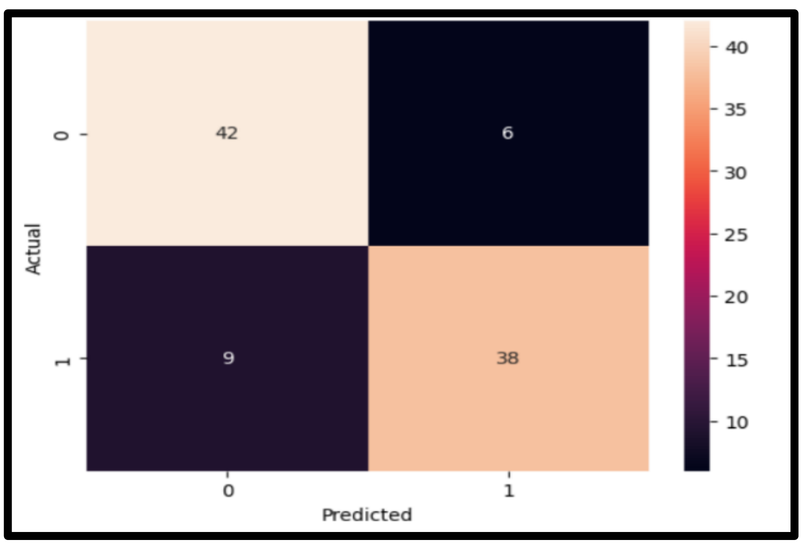


Table 2: Classification Report for Spam and Phishing Category

```
# printing classification report
print(classification_report(y_test , y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.88      0.85        48
           1       0.86      0.81      0.84        47

    accuracy                           0.84        95
   macro avg       0.84      0.84      0.84        95
weighted avg       0.84      0.84      0.84        95
```

HAM AND PHISHING EMAIL CATEGORY RESULT

We train our model and split into 80 % for training dataset and 20% for evaluation, figure 12 shows the confusion matrix and we can see that our email detector model detects 40 emails correctly as ham (0) and classifies 39 emails correctly as phishing (1). The accuracy of the model is 83%. However, Table 3 shows the “Recall”, “Precision”, and “F1-scores” for Ham and Spam category model performance.

Fig 12. Confusion Matrix for Ham and Phishing Custom Dataset

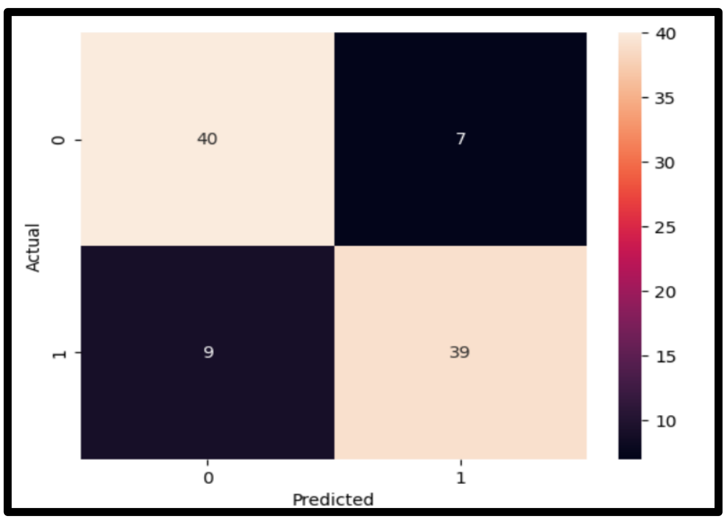


Table 3: Classification Report for Ham and Phishing Category

```
# printing classification report
print(classification_report(y_test , y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.85      0.83        47
           1       0.85      0.81      0.83        48

    accuracy                           0.83        95
   macro avg       0.83      0.83      0.83        95
weighted avg       0.83      0.83      0.83        95
```

Table 4: Model Evaluation Performance for Ham, Spam Phishing Category Classification Comparison Report

Category	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**Support**
Ham (0) and Spam (1)	86%	89% 84%	82% 90%	86% 87%	187 187
Spam (0) and Phishing (1)	84%	82% 86%	88% 81%	85% 84%	48 47
Ham (0) and Phishing (1)	83%	82% 85%	85% 81%	83% 83%	47 48

CONCLUSION

The Model evaluation Performance comparison report from table 4 shows that the accuracy of the model using the custom email dataset varies from 86%, 84% and 83% respectively. This is the same with the weighted average of each category where each performance value is weighted with the support column, and we use the weighted average to get the overall model performance. Our model's great performance is attributed to the BERT pre-trained model, which improves our email detector's ability to understand message context and allows better classification of spam, phishing, and ham (non-spam). On a wide range of tasks, the model outperforms conventional machine learning methods. We can see that spam is an enormous issue in the world of technology that costs consumers and companies financially. Emails and SMS messages may include viruses and phishing scams, which might result in identity theft. This problem is not only inconvenient, but also prohibitively expensive. In future work, the accomplished work can be improved by selecting a representative sample from various public email corpuses to train and evaluate the model, enabling businesses to develop their own email detectors.

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Measuring Emotional Intelligence Influences on Organizational Citizenship Behavior: Examining Gender's Role of Transformational Leadership in Higher Education

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ABSTRACT

This study investigates the impact of Emotional Intelligence (EI) and transformational leadership on Organizational Citizenship Behavior (OCB) in the context of higher education, with a particular focus on gender differences. Drawing on data from 134 faculty and staff members at two Florida public universities, the research employs a cross-sectional survey design to explore the interplay of these constructs. The findings reveal that transformational leadership significantly enhances the prediction of OCB beyond the relationship between EI and OCB alone. Notably, gender differences in OCB were found to be statistically insignificant. This study contributes valuable insights into the dynamics of EI, OCB, and transformational leadership within the higher education sector, emphasizing the evolving demands on academic leaders in the contemporary educational landscape.

Keywords: Emotional Intelligence, Organizational Citizenship Behavior, Transformational Leadership, and Higher Education

INTRODUCTION

Global economic, technological, cultural, and demographic factors continuously reshape the business landscape on a daily basis, and the higher education sector is not exempt from these influences. In public universities, the primary objectives of academic leaders typically revolve around advancing academic and student success and fostering excellence in teaching, scholarly endeavors, and public service. However, today, academic leaders in higher education also confront real-world issues and are expected to approach political and economic challenges with a business-oriented perspective. Despite the demand for leaders who can effectively inspire and influence a workforce, many national colleges and universities are ill-prepared to cultivate such academic leaders. Consequently, recruiting individuals capable of fostering innovation and effectively guiding a workforce becomes paramount (Collins, 2014).

Academic leaders bear the responsibility for the growth and development of their institutions and must engage their workforce in pursuit of their mission while upholding high ethical standards (Birx, 2019; Mohnot & Shaw, 2017). Analogous to leaders in the private sector, academic leaders within the public higher education domain must also demonstrate the ability to operate at peak efficiency levels, enhance revenue streams, and reinforce autonomy to distinguish themselves from mediocrity (Mohnot & Shaw, 2017). Research suggests that leaders with a heightened EI level demonstrate self-awareness, self-regulation, intrinsic motivation, empathy, and adept social skills. Importantly, EI has demonstrated a tangible impact on organizational outcomes within the business context (Goleman, 1995, 1998; Olcer et al., 2014). However, research is limited within the area of EI, OCB, and transformational leader impacts within higher education. Furthermore, research is even further limited when examining gender and the three constructs. This research aims to measure employee EI's influences on OCB through the mediating role of transformational leadership in higher education institutions and among gender. This paper has practical implications for higher education and related institutions. The remaining of this paper is the following: review of literature, research purpose, methods, results, and conclusion.

LITERATURE REVIEW

The Higher Education Industry

Significant transformations have occurred over the past century within higher education, which heightened three distinct trends: a shift from an exclusive elite model to mass participation and subsequently to universal access (Cantwell et al., 2018; Cooperman, 2014; Trow, 1970). The shift from an 'elite' system, catering to less than 15% of adolescent students, to a 'mass' system encompassing 15-50% of students, and finally to a 'universal' system with over 50% participation reflects this profound transformation (Cantwell et al., 2018; Scott, 2019). This “mass system” evolution in higher education represented an educational shift and triggered significant societal changes. The transition to mass higher education gave rise to tensions related to diversification, democratization, educational quality, equality, and cultural diversity and encouraged cross-border dialogues (Scott, 2019; Su & Wood, 2018).

Mass higher education systems often adopt a corporate governance style driven by increased political prioritization influenced by funding competition and other economic factors (Scott, 2019). Alongside these changes, challenges emerged, including larger class sizes, modularization, and reduced student interaction (Su & Wood, 2018). Today, public institutions are the most vulnerable as they face state funding reductions ((Powell et al., 2023), rising tuition fees, decreased student services, and were compelled to adopt an entrepreneurial mindset to navigate increased competition and secure alternative funding sources (Cantwell et al., 2018). Consequently, an increasing number of academic institutions have incorporated business-like and mass-marketing strategies historically associated with private-sector industries (Cantwell et al., 2018; CBPP, 2018). As a result, universal access to education has emerged as a global policy aimed at promoting economic development, achieving pay equality, and facilitating social mobility (Cooperman, 2014).

Moreover, the advent of Information and Communication Technologies (ICTs) has further pushed the “mass system” concept by transforming higher education’s landscape of knowledge dissemination and altering the teaching and learning methods. However, it is important to note that this expansion does not necessarily translate into a substantial increase in graduation rates. For example, in 2014, a public university in India achieved a remarkable milestone by offering a vast array of completed massive open online courses (MOOCs), with a staggering count of 3,000 courses and an enrollment exceeding three million students. Nonetheless, there is an ongoing debate about whether the rapid proliferation of MOOCs results in a dilution of the quality of higher education provided to such immense numbers of learners (Cooperman, 2014).

Governance of Public Higher Education Systems

The authority exercised by a university and that of the state in overseeing its operations and activities are substantially influenced by its governance framework, which exhibits variations from state to state. As time has progressed, the extent of state control over public higher education systems has come under scrutiny from taxpayers, who have expressed concerns about diminishing public participation (McLendon & Ness, 2003). Throughout the twentieth century, state governments' heightened level of involvement and interference in higher education has generated research inquiries and public discussions surrounding the diverse governance structures and their implications.

The National Center for Education Statistics (2019-a) reported a 25% increase in the number of public 4-year institutions since the academic year 2000-01. Over the past decade, there has also been a notable 36% growth in the total faculty count within public institutions. However, despite this expansion, the ratio of full-time students to faculty in degree-granting postsecondary institutions has experienced a decrease, shifting from 15:1 to 14:1 since 1999.

Thus, evaluating the performance of the 'mass' higher education system at the national level becomes challenging when considering the diverse landscape of 50 statewide operating systems (Hempsall, 2014). Furthermore, a decline in political prioritization and public funding for higher education and various challenges spanning social, economic, environmental, and governmental domains have contributed to an increasingly competitive, intricate, and unpredictable higher education environment (Cooperman, 2014; Scott, 2019). As a result, academic leaders must be aware of broader surrounding issues and be capable of effectively responding to the challenges of the “mass system” higher education era (Collins, 2014; Hempsall, 2014).

Academic Leadership

Within academia, individuals assuming leadership positions have traditionally been selected primarily for their academic and research achievements, with less emphasis on their demonstrated capacity to guide and oversee a workforce proficiently. Additionally, leadership roles within higher education are frequently assigned without well-defined career advancement pathways or structured training initiatives designed to cultivate effective managerial competencies (Hempsall, 2014).

Furthermore, the conventional practices associated with academic leadership are antiquated and do not align with the demands of the contemporary, intricate, and uncertain educational environment. Traditionally, readiness for academic leadership necessitates focusing on four distinct domains: academic, administrative, interpersonal, and global contextual. Specifically, the academic domain encompasses aspects related to teaching, learning, academic standards, and assessments. Meanwhile, the administrative domain includes qualities associated with effective management, the capacity to engage and connect with various stakeholders, and the ability to navigate the global educational landscape. Finally, the global contextual domain signifies a leader's capability to elevate the institution's position within the broader international educational and academic achievement contexts (Mohnot & Shaw, 2017).

Research by Hempsall (2014) interviewed 29 senior academic leaders regarding their role and responsible expectations of working towards success. They found that the majority of academic leaders felt the job expectations were more than one can handle. One can also conclude the same is for today as the “mass system” of higher education, COVID-19, the decrease in college-age students within America, and brought on more challenges for academic leaders. Thus, management skills are not enough. As a result, today’s academic leaders need transformational leadership skills.

Transformational Leadership

Transformational leadership is anchored in a leader-follower dynamic capable of positively influencing entire social systems. Leaders embody critical transformational behaviors, such as motivation, vision, and inspiration, profoundly affecting others to exceed their perceived capacities in pursuit of a common objective. Four core elements are typically delineated within the transformational leadership theory, denoted as the four I's: idealized influence (comprising attributes and behaviors), inspirational motivation, intellectual stimulation, and individualized consideration (Bass, 1985). The initial component, idealized influence or charisma, pertains to the emotional facet of leadership, wherein leaders serve as role models, inspiring followers to emulate their qualities. The inspirational motivation element involves effectively communicating and motivating followers to commit to the collective vision of the organization. Intellectual stimulation represents the third element, necessitating leadership that stimulates creativity and encourages followers to challenge themselves and others. The fourth component, individualized consideration, characterizes leaders who foster a supportive environment, allowing followers to express themselves freely and acknowledging their voices (Northouse, 2019).

Emotional Intelligence (EI)

Organizations are fundamentally social entities where individuals constantly interact, and gaining insights into emotions within the workplace can provide a range of advantages for an organization. While cognitive intelligence, as assessed by the intelligence quotient (IQ), gauges an individual's intellectual capabilities (Thorndike, 1920), EI represents a form of social intelligence that involves the cognitive ability to perceive, evaluate, and express emotions effectively to motivate oneself and others (Goleman, 1995; Salovey & Mayer, 1997; Thorndike, 1920). It is important to note that IQ and EI engage distinct brain processes, and relying solely on IQ as a predictor of job performance for individuals and work teams is inadequate (Coetzer, 2016; Goleman, 1995; Salovey & Mayer, 1990).

Organizational Citizenship Behavior (OCB)

Similar to Emotional Intelligence (EI), Organizational Citizenship Behavior (OCB) is a psychological construct denoting an individual's engagement in voluntary contributions that are not contingent on an enforceable reward system (Cheung & Cheung, 2013; Turnipseed, 2018). OCB signifies an employee's willingness to go beyond their job requirements, and research has indicated that an individual's level of EI can influence their propensity for engaging in citizenship behaviors (Organ, 1997; Organ, 1988; Tofighi, 2015; Turnipseed, 2018). The significance of OCB within the higher education industry lies in its potential to positively impact the survival of academic institutions (Tambe & Shanker, 2014). In an era characterized by rapid change, public higher education institutions must invest in the development of future educational leaders and enhance workforce efficiency (Collins, 2014). Transformational leadership, known for its capacity to inspire and motivate, has also been found to have a positive influence on employee citizenship behaviors and work attitudes (Olcer et al., 2014). These concepts—Transformational leadership, EI, and OCB—hold relevance in the workplace, examining employee behaviors and their potential to enhance institutional effectiveness, all without incurring additional investment costs or resource requirements (Cheung & Cheung, 2013; Turnipseed, 2018).

EI, OCB, and Transformational Leadership in Higher Education

Emotional Intelligence (EI) and Organizational Citizenship Behavior (OCB) represent two behavioral constructs that have been demonstrated in previous research to exert a positive influence on job satisfaction and motivation (Goleman, 1998; Burns, 1978; Organ, 1997; Hempsall, 2014; Kumar, 2014). Moreover, transformational leadership behaviors have been associated with influencing employee citizenship behaviors, both directly and indirectly (Jain & Duggal, 2016). Research on EI and transformational leadership has consistently supported the notion of enhancing satisfaction, commitment, and overall organizational effectiveness (Jain & Duggal, 2016; Kumar, 2014). More specifically, the moderating relationship of EI in relation to leadership styles and organizational commitment has been highlighted in the literature (Saleem et al., 2017).

Strategic investments in human capital through employee training and development programs are integral components of organizational strategies. Numerous studies have provided evidence of the positive correlation between a leader's EI and the effectiveness of transformational leadership in enhancing employee engagement and OCB (Majeed et al., 2017; Milhem et al., 2019).

Further noteworthy advancements in leadership research encompass the substantial correlation between transformational leadership and the constructs of EI, which aids in heightened employee organizational satisfaction, commitment, and overall effectiveness (Hempsall, 2014; Kumar, 2014; Martinez et al., 2018). Transformational leaders exert an indirect influence on employee citizenship behavior through the perception of fairness and justice. Essentially, the stronger the perception of a leader's transformational leadership capabilities, the greater the measured OCB (Khalili, 2017; Martinez et al., 2018).

Currently, there have been a few studies on EI, OCB, and Transformational Leadership in general. However, their research is limited and divided, with conflicting results, if any, regarding the perceived transformational leadership effect on EI on OCB in higher education and gender.

RESEARCH GOAL AND PRESENTATION

The overall goal of this research is to measure employee EI's influences on OCB through the mediating role of transformational leadership in higher education institutions and among genders. Specifically, this paper seeks to study and answer the following research question:

- Does perceived transformational leadership affect the relationship between EI and OCB in higher education and via their gender?

METHODS

This quantitative research, firmly rooted in scientific research methodologies, adheres to a positivist paradigm, characterized as a worldview perspective on research. Within the positivist paradigm, the primary aim is to systematically and objectively explore measurable cause-and-effect relationships (Kivunja & Kuyini, 2017).

The research employed a cross-sectional survey design, which involves collecting data at a single point in time (Creswell & Creswell, 2018). This survey design was deemed suitable for the study as it enabled the investigation of relationships between variables. This quantitative study employs a survey research design, data were gathered through an electronically structured questionnaire. Approximately 1,000 faculty and staff members from two Florida Public Universities were contacted via email, inviting them to participate and requesting their consent before commencing the survey. The online survey was conducted using the Qualtrics platform to collect data from the targeted population. The Qualtrics online survey incorporated the following self-report instruments: the Wong and Law Emotional Intelligence Scale (WLEIS) (comprising 16 items), the adapted Multifactor Leadership Questionnaire (MLQ) rater report (20 items), and a demographic questionnaire (Podsakoff et al., 1990; Wong & Law, 2002; Xirasagar et al., 2005). The adapted MLQ instrument allowed the researcher to evaluate the influence of perceived transformational leadership behaviors on employee EI.

Participants provided responses to survey questions on a Likert scale, and the data was collected and recorded using the Qualtrics platform. Additionally, demographic data, including gender, was collected.

Data was cleaned to ensure no duplicates existed within the data set. Data was analyzed via IBM's SPSS software.

Participants

This research study selected two public educational institutions in Florida, both of which are research-oriented and provide a comprehensive array of undergraduate majors, master's, and doctoral degree programs. The two universities were selected because the author had connections with the universities.

The study invited faculty and staff members from two colleges within these universities who reported either to an academic leader or a faculty member holding a leadership role to participate. The sample encompassed a wide range of employees, considering factors such as age, gender, and years of professional experience, and all participants were at least 18 years old. No additional exclusion criteria were imposed on potential participants for this study.

The appropriate sample size for this study was determined through a power analysis, which assesses the likelihood of achieving statistical significance (Cohen, 1988). The power analysis method is commonly applied in various statistical procedures, such as t-tests, analysis of variance, correlations, chi-square tests, and multiple regression analysis (Cohen, 1988; Lunenberg & Irby, 2008). The effectiveness of the power analysis is contingent upon factors such as the chosen significance level, the reliability of sample results, and the effect size (Cohen, 1988; Lunenberg & Irby, 2008).

The power analysis was conducted using the G*Power 3.0.10 calculator for this study. Out of the 1,000 faculty and staff members from Florida public higher education institutions who were invited to participate in the survey, a total of 134 individuals comprised the final sample size. The sample size ($n = 134$) was determined with parameters set at a 95% power level and a significance level of α .05, assuming an effect size of 0.3. Moreover, there was a total of 52 males and 98 females participating in this study.

RESULTS

Prior to testing the data set, all three variables were checked against several assumptions to ensure valid results when administering the hierarchical multiple regression. For this analysis, the dependent variable is OCB. In adding the two independent variables, EI and transformational leadership, to the regression equation in this particular order, it determined whether each variable contributed to the prediction of OCB. The multiple regression tested for several assumptions. First, an independence or 1st-order autocorrelation test verified that the variables were unrelated (Fox, 2016). The observation determined there was independence of residuals, as assessed by a Durbin-Watson statistic of 1.839. The partial regression plots showed a linear relationship between the EI, OCB, and transformational leadership variables. There was also homoscedasticity, as assessed by the visual inspection of a plot of OCB versus EI values and a plot of OCB versus transformational leadership values.

An examination of correlation coefficients and tolerance/VIF values identified whether multicollinearity existed among the variables. Neither of the independent variables had a correlation larger than 0.7, and the tolerance and VIF values were greater than 0.1 (the lowest is 948). The data set did not contain any high leverage or influential values. One case was identified as a potential outlier but was kept in the data because it was not an extreme outlier, with a standardized residual of 3.158. Also, the residuals were normally distributed in an inspection of a histogram and P-P Plot.

To test the research question, two separate hierarchical multiple regressions provided a comprehensive response to research question four. The first hierarchical multiple regression model presents OCB as the dependent variable, with EI and transformational leadership added as the two sequential independent variables. The second hierarchical multiple regression model presents EI as the dependent variable, with OCB and transformational leadership added as the two independent variables.

The first hierarchical multiple regression showed two models. The OCB variable variation explained by the EI and transformational leadership variables measured by R^2 was 28.9% and 33.7%, respectively. Model 1 resulted in an adjusted R^2 of 28.4%, while the adjusted R^2 for the second model was 32.8%, a medium-size effect, according to Cohen (1988). In adding the transformational leadership variable to the regression (Model 2), the change in R^2 increased by 4.8%. Table 1 presents the model summary with OCB as the dependent variable.

Table 1: Hierarchal Multiple Regression Model Summary – OCB Dependent Variable

Model Summary[c]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.538[a]	0.289	0.284	9.88413	0.289	60.240	1	148	0.000	
2	.580[b]	0.337	0.328	9.58003	0.048	10.545	1	147	0.001	1.839

Note. a. Predictors: (Constant), EI
b. Predictors: (Constant), EI, Transformational Leadership
c. Dependent Variable: OCB

The second hierarchical multiple regression presents EI as the dependent variable, with OCB and transformational leadership added as the two sequential independent variables. In adding the transformational leadership variable to the test, the R^2 increased by 0.3% from Model 1 to Model 2. Table 2 presents the model summary with EI as the dependent variable.

Table 2: Hierarchical Multiple Regression Model Summary – EI Dependent Variable

Model Summary[c]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.538[a]	0.289	0.284	8.82090	0.289	60.240	1	148	0.000	
2	.540[b]	0.292	0.282	8.83462	0.003	0.541	1	147	0.463	2.139

Note. a. Predictors: (Constant), OCB
b. Predictors: (Constant), OCB, Transformational Leadership
c. Dependent Variable: WLEIS

As illustrated in Tables 1 and 2, both hierarchical multiple regressions determined that adding the transformational leadership variable improved OCB and EI's prediction above the relationship between OCB and EI alone. The full model of EI and transformational leadership to predict OCB (Model 2) was statistically significant, $R^2 = .337$, $F(2, 147) = 37.335$, $p < .001$, adjusted $R^2 = .328$. Additionally, in the full model of

OCB and transformational leadership to predict EI (Model 2) was statistically significant, $R^2 = .292$, $F(2, 147) = 30.297$, $p < .001$, adjusted $R^2 = .282$.

Finally, a one-way ANOVA determined whether OCB levels were different among genders. The OCB levels increased from the male group ($n = 52$, $M = 139.80$, $SD = 10.23$) to the female group ($n = 98$, $M = 143.27$, $SD = 12.26$). Levene's test for equality of variances displayed a homogeneity of variances ($p = .116$). There were no statistically significant differences in OCB score between the gender groups, $F(1, 148) = 3.033$, $p = .084$.

CONCLUSION

In exploring employee behaviors in the workplace, this study evaluated the employees' EI and OCB and whether perceived transformational leadership had a measurable impact. The findings added to the limited body of literature surrounding this topic. It is important to note that his study is not without limitations. First, this study utilized and assessed the self-report questionnaires of employees to measure the three constructs. Next, it was limited to a small sample size. Second, the data was limited to two public Higher education institutions located in Florida. Future studies should address these limitations and expand on different demographic information. While this study had limitations, it does provide a practical impact for higher education institutions and related organizations to consider when hiring academic leaders.

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Investigation of Interpersonal Competencies in Early-Career Mutual Insurance Professionals

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ABSTRACT

A problem exists between employers and individuals as employers seek to hire individuals with non-technical skills who can add value and leadership to their companies. These non-technical skills are hard to recognize and identify when interviewing candidates. The researcher further defined, clarified, and investigated interpersonal competencies among early-career insurance professionals. The research was conducted through semi-structured interviews with 16 mutual insurance executives and two focus groups each consisting of five mutual insurance executives. These executives were selected and volunteered from five Pennsylvania mutual insurance companies. Interviews were transcribed and coded to find recurring themes pertaining to the competencies needed in early career insurance professionals. Controlling emotions was the most desired competency from insurance professionals. As these professional's converse with customers and coworkers on a daily basis, controlling emotions and de-escalating potentially confrontational conversations is essential. Verbal and written communication and collaborative teamwork were the next, most recurring competencies necessary for early career insurance professionals to possess. This research benefits employers in their hiring practices and in identifying insurance professionals for leadership and promotion opportunities.

Keywords: interpersonal competencies, insurance, communication, teamwork, competence

INTRODUCTION

Historical Perspective

Thomas Friedman, a renowned New York Times editor, began his 2011 address at the National Governors Association Annual Meeting by stating that the idea of parents wanting their children to live better than they do, may be in serious peril (National Governors Association Annual Meeting, 2011). He indicated it is no longer acceptable to be an average worker. The typical workday for the workforce will not suffice anymore. Average workers are being replaced by machines and foreign workers, who can do the job better and cheaper.

Similarly, a recent study in the United Kingdom (UK) job market, shared that the notion of only one education, one career, and one pension is gone (UK Commission for Employment and Skills, 2014). Today's young adults must find their own unique value to add to the world and careers, finding better ways to do their job. They will discover that their career path will evolve and change. For example, many jobs are no longer being accomplished at an office or company but are mobile or remote. Friedman affirmed that students must create their own jobs, or they risk becoming unemployment casualties (National Governors Association Annual Meeting, 2011). Creativity and innovation in our educational system is essential to propel it to the leading spot again. How can our young people bring value and thrive in their careers?

There is a significant skills gap between recent college graduates and their immediate job performance (Abas-Mastura, Imam, & Osman, 2013; Bradberry & Greaves, 2009; Burning Glass Technologies, 2015). This gap has been recognized for the last few decades a

Glass Technologies, 2015). This gap has been recognized for the last few decades and continues to be a problem with current employers. Employers show concern for finding specific skills in job candidates and matching the talent with the interviewee (Hart Research Associates, 2016; Manyika, Lund, Robinson, Valentino, & Dobbs, 2015; UK Commission for Employment and Skills, 2014).

Secondary schools, colleges, and universities are lessening the gap with improvements to curriculum and a plethora of outside influences such as internships, community involvement, cooperative education programs, professional development, and career days (Chiu, Mahat, Rashid, Razak, & Omar, 2016). As higher education institutions connect with community business leaders, recent college graduates will become more productive and successful in their occupations (Walker & Black, 2000; Yan, Yinghong, Lui, Whiteside, & Tsey, 2018). As this connection occurs between education, secondary or higher education, these skills, including soft skills, will transfer to the workforce (Chiu et al, 2016).

Today's employers know the skills they desire from their future employees (Burning Glass Technologies, 2015). Do current business school graduates have those skills? What are they? For the last decade, companies have not been shy about the need for their new employees to have people skills--skills that are hard to define (Burning Glass Technologies, 2015; Matteson, Anderson, & Boyden, 2016). This study investigates this task and answers these questions.

Insurance Connection

The insurance industry was chosen for this study for several reasons. Similarly, with business professionals retiring in the coming years, the insurance industry is experiencing an enormous talent gap crisis (Karl & Wells, 2016). This talent gap has been recognized and identified in the insurance industry, as well as the entire business workforce (Cole & McCullough, 2012; Duett, Baggett, Pappanastos, & Hamby, 2017; Karl & Wells, 2016). The need for new insurance professionals who will fill the place of retired insurance professionals is valid (Cole & McCullough, 2012). Quality succession of insurance professionals is crucial for this next generation of the insurance industry (Cole & McCullough, 2012).

The insurance industry consists of professionals with a diverse set of personality types and jobs (Cassidy, Marshall, & Hollman, 1998; Gallagher, 2019; Kwon, 2015). For example, an insurance salesperson's personality is outgoing and gregarious versus an insurance underwriter's personality being more analytical and logical (Cassidy et al., 1998; Gallagher, 2019). This is a further reason for using the insurance industry as a representative sample for business professionals.

As jobs are filled with productive insurance professionals, there is a need for a process to identify quality, new hires. Specific interpersonal and emotional intelligence competencies, common among successful early-career insurance professionals, were identified as this research investigated emotional intelligence within the insurance industry.

STATEMENT OF PROBLEM

A dilemma exists in employers finding professionals with emotional intelligence who add value and leadership to their companies (Burning Glass Technologies, 2015; Matteson et al., 2016). Discovering and defining those skills in quality interviews and development of new-career professionals is a struggle (Burning Glass Technologies, 2015; Matteson et al., 2016). For example, quality communication skills are commonly shared as a requirement in a new business professional. Communication skills encompass a plethora of facets, including verbal, nonverbal, written, and presentation skills. Which specific communication skill is necessary for new career hires in the business or specifically, the insurance industry? The workforce is at a critical stage where soft skills, including interpersonal competencies, are necessary for successful, new-career business professionals (Bambacas & Patrickson, 2008; Matteson et al., 2016).

Social skills have become more defined and held in higher esteem in recent years, but more work is necessary to further define and assist employers to identify those skills in interviews for future professionals, as well as those who are recent college graduates looking for a professional career (Matteson et al., 2016; Prati, Douglas, Ferris, Ammeter, & Buckley, 2003). For example, teamwork is a recent and essential skill present in most businesses today (Prati et al., 2003). How does one recognize those team skills in a new or anticipated hire? How does one develop those skills to share in an interview?

The research investigated this dilemma and defined specific examples of these interpersonal competencies, soft skills, and emotional intelligence which are necessary for successful employees contributing value to their organization and investigated the framework for interpersonal and emotional intelligent competencies in the field of business, specifically the insurance industry.

PURPOSE OF THE STUDY

The purpose of this study was to investigate the interpersonal and emotional intelligence competencies associated with early-career professionals in the insurance industry. As interpersonal competencies and emotional intelligence were investigated, precise definitions were shared to assist both recent business graduates and employers in the insurance industry. This study adds to the growing research in this area of interpersonal competencies and emotional intelligence needed in early-career insurance hires. The research questions used for this study were:

Research Question 1: What interpersonal competencies are sought in early-career insurance professionals?

Research Question 2: What emotional intelligence and interpersonal competencies are necessary for early-career insurance professionals as an early indicator of professional success?

SIGNIFICANCE OF THE STUDY

Recent studies of employers and employees show a substantial relationship between satisfactory job performance and competence in employability skills, including emotional intelligence (Abas-Mastura et al., 2013; Chan, Ahmad, Ngadiman, & Omar, 2015). This study sought to identify those employability skills and further develop methods for improving the identification of those skills in the interviewing process and training development. As employability skills are identified, employees are equipped to develop into successful leaders within their institution.

In the Abas-Mastura et al. (2013) study, employers identified personal management, teamwork skills, positive behavior management as desirable traits of their constituents. A similar study found that "American adults and employers wanted colleges to produce graduates who can think critically and creatively and can communicate verbally and in writing" (Desai, Berger, & Higgs, 2016, p. 10). These employability skills improve job performance and effectiveness in the workplace. Employers are desperate and often find it difficult to find these skills in their new-career hires. The employees exhibiting these skills may rapidly move ahead in their careers with a huge amount of success (Abas-Mastura et al., 2013).

The insurance companies used in this research should benefit from this study by assisting in developing their interviewing protocol to attract and find top talent. Another area of value this study may have been adding to the literature in solving the talent gap crisis in the insurance industry.

ASSUMPTIONS

Several assumptions to this study must be noted. First, the assumption that all insurance executives believe that interpersonal competencies and emotional intelligence are necessary for early-career professionals is important to acknowledge. Interpersonal competencies or emotional intelligence is not assumed by all employers as an important characteristic in their professional staff.

Secondly, interviewees might have answered in a way to help or assist the researcher in their own form of a biased nature. The answers of the interviewees may have been skewed to support the research questions leading to the third assumption that all interviewees answered the questions honestly and candidly. The fourth assumption of the researcher is that interpersonal and emotional intelligence competencies are integral for the success of early-career insurance professionals as an outcome of this study. Lastly, the researcher assumes that as early-career insurance professionals progress in their career they increase those interpersonal and emotional intelligent competencies. In order to control bias, interview questions were adapted from a pilot study of a similar topic in the engineering industry (Handley, 2017). Permission was granted to adapt and use these interview questions (M. Handley, personal communication, December 14, 2018).

THEORETICAL FRAMEWORK

While cognitive skills, e.g. memory and thinking skills, are important to both workplace and academic institutions, non-cognitive skills, including emotional maturity and interpersonal skills, are becoming increasingly in demand for success and promotion in the workforce (Kyllonen, 2013). Goleman is credited with giving emotional intelligence and non-cognitive skills exposure as essential skills for business professionals. (Seal, Boyatzis, & Bailey, 2006). There is “a different way of being smart” (Goleman, 1998). Emotionally intelligent individuals outperformed their academically intelligent colleagues who lacked emotional intelligence (Goleman, 1998).

Goleman’s work is the groundbreaking foundation for developing an emotional competence framework (Goleman, 1998). This research used the theoretical framework based on Goleman’s (1998) emotional intelligence theory and competency framework as a basis. Since the purpose of this research investigated the interpersonal and emotional intelligence competencies associated with early-career professionals in the insurance industry, Goleman’s framework and research lends itself naturally to be the theoretical framework for this study. The research questions seek to investigate the interpersonal and emotional intelligence competencies desired by business professionals at a greater level in the insurance industry. Goleman’s framework is shown below in Table 1-1.

Table 1 Goleman's Emotional Competence Framework

Characteristic	Description
Personal	
competence	Identification of one's emotions and
Self-awareness	strengths.
Self-regulation	Controlling and adjusting one's emotions.
Motivation	Determined to achieve one's goals.
Social	
competence	Sensitive toward other's feelings.
Empathy	Influencing others toward cohesiveness.
Social skills	

Source: Adapted from Goleman, (1998).

LITERATURE REVIEW METHODOLOGY

Research for this study was conducted in two stages. The first stage was conducted November 2018 to January 2019. This stage began with searches of terms "emotional intelligence" and "workforce," "interpersonal competencies" and "emotional intelligence," and "interpersonal competencies" and "employees." The "emotional intelligence" and "workforce" search yielded 19,400 results for scholarly and peer-reviewed articles. The "interpersonal competencies" and "employees" search resulted in 2,150 articles. The results were 1,250 articles for the "interpersonal competencies" and "employees." Stage two literature search began February 11, 2019, to March 2019 with the search words "emotional intelligence" and "insurance professionals." This search led to the result of 44 articles. An added search of "finance industry" "emotional intelligence" yielded 317 articles to focus on the finance sector where insurance is a portion. Research was used extensively through the Pennsylvania State University (https://libraries.psu.edu/) and the Bloomsburg University (http://library.bloomu.edu) libraries' comprehensive data systems. Special emphasis was given to current articles written after 2005. Extensive analysis of the references of comparable dissertations was conducted. Further relevant references were the result. As the articles were collected, abstracts were examined to determine the relevance to the literature review and its themes. Approximately 80 articles were used in this literature review.

Interpersonal Competencies in the Workplace

As the industrial revolution and mass production era came to a close around the 1970s, the American way of training and development shifted (Robles, 2012). The shift from narrow and simplistic skills to more interpersonal and complex skills evolved (Carnevale & Smith, 2013; Lavy & Yadin, 2013; Robles, 2012). The technical skills did not completely vanish, but interpersonal skills emerged, complementing the existing technical skills (Lavy & Yadin, 2013). These interpersonal skills mainly dealt with human interaction components (Lavy & Yadin, 2013).

Competition expanded which demanded more variety, customization, and convenience within the products and services that business provided to customers. New employee skills emerged as a necessity to flourish in one's career. These skills included problem solving, communication, and behavioral talents (Carnevale & Smith, 2013).

New terms developed for these skills including soft skills, employability skills, non-cognitive skills, and interpersonal skills. Interpersonal skills are occasionally used interchangeably with soft skills (Matteson et al., 2016). Recent studies stated that soft skills were shown to be an integral part of the success of an individual as IQ or standardized achievement tests (Heckman & Kautz, 2012; Kyllonen, 2013; Mitchell, Skinner, & White, 2010; Schulz, 2008).

Soft skills were found to be a central need in accounting professionals (Kermis & Kermis, 2010). Kermis and Kermis (2010) found that the accounting professional, usually detail oriented and technical in nature, is not sufficient to produce a quality employee. Employees need to be competitive and competent in their profession, need to possess soft skills (Kermis & Kermis, 2010; Mitchell et al., 2010; Shrivastava, 2013).

A European study analyzed the quality of the workforce and how recent college graduates can meet the needs of their future employers (Andrews & Higson, 2008). Interpersonal competencies or soft skills surfaced as one of the top concerns among employers in research studies (Andrews & Higson, 2008; Finch, Hamilton, Baldwin, & Zehner, 2013; Hodges & Burchell, 2003; Ibrahim et al., 2017; Mitchell et al., 2010). Similarly, the graduates who were interviewed shared that specific skills, such as verbal and written communication, teamwork, and social skills, were imperative for their future employment and success in the workplace (Andrews & Higson, 2008). Robles' (2012) study "identified the top ten soft skills as perceived by business executives are integrity, communication, courtesy, responsibility, social skills, positive attitude, professionalism, flexibility, teamwork, and work ethic" (p. 453).

Comparably, a national survey shared the top skills employers continually demand from their constituents are listening and verbal communication, resolving conflicts creatively, confidence and pride in their work, interpersonal competencies, and leadership potential (Goleman, 1998). Interpersonal competencies exhibited in supervisors, who are leaders in the workplace, show them to be a successful and effective piece of the workforce (Bambacas & Patrickson, 2008; Hunt & Baruch 2003).

When employers are in the process of hiring, their decisions are influenced by four factors of hard skills, soft skills, appearance, and others (Griffin, Cangelosi, & Hargis, 2014; Robles, 2012; Whitehurst, 2016). Soft skills are the most important factor which are also called “people skills” (Hodges & Burchell, 2003; Mitchell et al., 2010; Schulz, 2008). These skills comprise an individual’s temperament, communications skills, and amiability (Griffin et al., 2014; Schulz, 2008). In contrast, Robles (2012) shared that people skills are only one part of soft skills and should not be quoted interchangeably. Another study found that the top skills employers wanted from their new hires were communication, analytical, computer, adaptability, interpersonal, leadership, diversity awareness, planning, problem solving and teamwork skills (Hansen & Hansen, 2010).

Of the five characteristics of strong work ethic, integrity, communication skills, dependability, and dedication, work ethic scored the highest in a study with 244 college students who were already employed (Griffin et al., 2014). Work ethic is an applied philosophy of strong, diligent effort in one’s career. Integrity was a strong second to the qualities that employers found the most desired. Integrity values honesty and uprightness (Griffin et al., 2014). The third scoring characteristic was communication skills which include verbal and written (Griffin et al., 2014).

Similarly, a recent study with 438 employers from a plethora of industries answered questionnaires involving the five dimensions of soft skills including basic knowledge, communication skills, practical skills, leadership, and attitude of a specific, European university (Chiu et al., 2016). Interpersonal competencies and non-cognitive skills are vital requirements for success in the workplace.

SUMMARY

This paper provided a historical perspective and background for the basis of this research. The chapter established an important connection to the insurance industry, where interviewees will be selected. The problem statement shared the necessity for defining interpersonal and emotional intelligence competencies in depth to provide quality employees to insurance professionals. The problem led to the purpose of this study of exploring the interpersonal and emotional intelligence competencies associated with early-career professionals in the insurance industry. The significance of the study was discussed, adding to current literature and further clarifying the definitions of interpersonal competence and emotional intelligence for employers. Goleman's research provides the conceptional framework which connects to the research questions and purpose of this research. The paper concludes with definitions used throughout the research for clarification.

DEFINITIONS

For this study, interpersonal competency, employability skills, and soft skills are used interchangeably. As the research was conducted, many of the studies used these terms synonymously. For clarification in this study, common terms used in this study included:

- Competence – Competence refers to showing superior performance, exhibiting effective job performance, and the ability to perform and finish a task (Moore, Cheng, & Dainty, 2002).

- Competency – Competency is defined as characteristics of an individual related to their job performance (Hodges & Burchell, 2003). Competency is also referred to "a capability or ability that leads one to successful outcome" or appropriate behaviors that lead to success in one's workplace (Seal et al., 2006). An operational definition of competency in the workplace is a combination of technical or cognitive skills and personal behaviors (Hodges & Burchell, 2003). Personal behaviors include attitudes, values, and beliefs (Hodges & Burchell, 2003). Positive competencies lead to superior job performance.
- Interpersonal competency – another similar term used interchangeably is people skills and characteristically is a person's relationship with others (Robles, 2012). Interpersonal competencies are a portion of soft skills (Robles, 2012). Interpersonal competencies promote customer service and positive attitudes, communicating effectively and respectfully (Robles, 2012).
- Critical thinking – intelligently processing information with a defined purpose in order to solve a problem or draw conclusions without prompt (Desai et al., 2016).
- Soft skills – Soft skills are similar to interpersonal skills which include social skills as opposed to hard skills, including technical skills. Soft skills are known to include teamwork, cooperation, listening, positive attitude, conflict resolution, social intelligence, communication, and ethics, and are vital for success in one's professional career (Anthony & Garner, 2016; Hurrell, Scholarios, & Thompson, 2013; Ibrahim, Boerhannoeddin, & Bakare, 2017; Shakir, 2009; Whitehurst, 2016). Soft skills include interpersonal or people skills and personal or career attributes (Robles, 2012).

- Emotional intelligence – According to Bradberry and Greaves (2013), emotional intelligence encompasses the four skills of self-awareness, self-management, social awareness, and relationship management. Anand and UdayaSuriyan (2010, p. 1) defined emotional intelligence as “the ability to perceive and express emotion to stimulate thought, understand, and reason. It regulates emotion in oneself and others.” Emotional intelligence is the ability to manage one’s emotions (Abraham, 1999; Côté, 2014; Prati et al., 2003). Emotional intelligence is also defined as “the ability to read and understand others in social contexts, to detect the nuances of emotional reactions, and to utilize such knowledge to influence others through emotional regulation and control” (Prati et al., 2003, p. 21).

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Development of Conceptual Models to Enhance the Technology Threat Avoidance Theory (TTAT) Framework

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ABSTRACT

This paper is intended to serve as a conceptualization framework to enhance the Technology Threat Avoidance Theory (TTAT) framework. The foundational conceptualization of enhancing the TTAT framework is proposed with an additional possibility of construct variation to enhance threat avoidance standards to provide a more enhanced view of the theory for researchers, practitioners, and policymakers to provide a new interpretation of exploration that is more encompassing of environmental issues to diverse audiences. Conceptual models can provide a tool to provide a visual representation of specific research questions, where the critical component enhancement of TTAT will enhance cyber programs, practices, and policies designed to promote security hygiene and business capabilities. Additionally, this conceptual model provides enhancement and improved guidance for threat avoidance principles that can counter efforts to utilize cybersecurity technology to mitigate threats that present an inherent risk to organizational socio-economic stability. The TTAT model contains inherent gaps emerging due to the 2020 COVID-19 pandemic to enrich the practical understanding of this conceptualized framework. Research findings may influence future cybersecurity posturing, practices, and policies. This enhanced conceptual model of TTAT can assist others in framing diverse threat avoidance philosophies, theories, and cybersecurity conceptualized frameworks in innovative and potentially transformative ways.

Keywords: conceptual model, conceptual framework, technology threat avoidance theory, cybersecurity, end-user behavior, cyber threats, COVID-19

INTRODUCTION

As organizations face accelerating cybersecurity challenges, requirements for policy implementation and reform, and mitigation efforts, it is imperative that the efforts in implementing mitigation strategies, including continuous monitoring and adaptability, are considered not only practically but should also designed in tandem with conceptual understanding to enhance frameworks to meet the current challenges. Safeguards implemented with conceptual and practical applications are crucial not only for safeguarding digital assets and personal and proprietary information but also for ensuring the seamless operation of the organization. Organizations are increasingly susceptible to robust and dynamic threats, and threat deterrence can be seen as proportional to an organization's cybersecurity mitigation strategy budget (DeFleice, 2021). Cybersecurity budgets are motivated by perceptive end-user response and viable risk factors to the organization. The viability of response and risk can substantiate technological incorporation where the return on investment (ROI) is critical based on event saturation and cost-of-measure functionality (Fielder et al., 2018). However, the increased complexity of cybersecurity risk substantiation in the form of monetary ROI and end-user perception can rapidly deteriorate the comprehensive indoctrination of specific federal control requirements or recommendations. Cybersecurity professionals have to circumnavigate user-perceived valuations and various organizational complexities due to distributed workforce constructs, where reflective indoctrination of practical security technologies withstanding scalable long-term events can lead to excessively adverse events to organizational sovereignty within cybersecurity (Nickle, 2023).

RESEARCH GOAL

In a qualitative grounded theory analysis, Nickle (2023) provided insight that constructs comprised descriptive end-user behavioral viability derived from availability, event correlation to COVID-19, indoctrination due to threat advancement and technological development, and cost-of-function measures. The findings noted that the current TTAT framework was lacking. TTAT supports the analysis of individual user behaviors, ultimately highlighting the compelling requirement for identity-based micro-segmentation within the framework of conventional models, with the approach to counteract various threat variations during different scenarios (Nickle, 2023). The objective of the present article is to discuss further the implications of adding a new understanding of the TTAT framework, enriching the framework to include natural and manufactured disasters, public health crises (pandemics), the impact of climate change, technology and electrical failures, and humanitarian crises which impact the response of both the organizations and users technical stability.

LITERATURE REVIEW

The literature review delved into the concepts of Micro-Segmentation, the NIST Cybersecurity Risk Framework, the MITRE ATT&CK Framework, Least Privilege, and Network Segmentation. These specific domains collectively establish the core framework upon which the focus and test of the use of Zero Trust Technology in the perspective of the TTAT framework is built. The scope of the literature review concentrated on subjects delineated by a historical examination, overlapping domains of interest, and cost-related strategies tailored for expansive operational environments using a Technology Threat Avoidance Theory (TTAT) lens.

The TTAT developed by Liang and Xue (2010) fundamentally describes the state of end-user activity and engagement to negate or avoid subjectively. The TTAT theory's subjective processes aim to target users' fundamental and behavioral mechanisms through analytical variances that determine the self-efficacy of the measure of defense/avoidance via user perception (Peng, et al., 2021). In addition, the TTAT theory is supported by various studies, such as that by Mei-Hui Peng and Hsin-Ginn Hwang (2021) in the empirical study of an integrated conceptual adoption framework based on

TTAT and the corresponding study by Willie C. Session (2022), noting that TTAT factors influence cybersecurity professionals' willingness to share information. The studies postulated and proved that TTAT can serve as a real-world construct for determining viable threat vectors, attack surfaces, and ideological aims to interface an organizational substructure for malicious intent. However, TTAT fails to consider critical individual differences when assessing avoidance motivation. The avoidance motivation has been found to extend to zero-trust technology implementation, as found in Nickle's (2023) qualitative study detailing the avoidance of execution of zero-trust technology.

As many theories once fabricated mechanisms based on a wide array of terminology or circumstantial intent, the TTAT substantiates user mannerisms through various physiological and psychological parameters based on risk analysis, psychological dispositions of health, prevention cost, and perceptive/motivational processes (Liang & Xue, 2010). Thus, the TTAT framework can apply to various circumstances that host defense mechanisms based on human behavior and be applicable to various user analytical behaviors (Liang & Xue, 2010). Although the desire is to boost IT security and methodologies, this theory aims to add to the avoid-approach theory that was once neglected due to threat gaps and substantiative evidence that threat avoidance is instinctually different from posturing safeguards (Peng, et al., 2021). The associated thought process can be applied to various industry verticals and business risk techniques based on the refined process where interactive actions or perceptions can substantiate an avoidance motivation and behavior (Liang & Xue, 2010).

Conceptual Methodology of TTAT (+) Framework

The grounded constructs of phenomena and subjective processes of the TTAT model aim to target user fundamental and behavioral mechanisms through analytical variances that determine the self-efficacy of the measure of defense/avoidance via user perception (Peng, et al., 2021). As modern security principles inherently misalign due to risk tolerance and social influence of the TTAT framework (Liang and Xue, 2009), there is a subjective foundational concept that strategic technological indoctrination and motivation strategy combined with event modeling and control frameworks can inherently influence end-user behavior deterministic on a singular foundational event. The event specifically indeterminately substantiated a comprehensive market shift due to dynamic threat variants not purely addressed in the parameters of the findings of Liang et al. (2010), Peng et al. (2021), Session (2022), and Taherdoost (2022). The findings of Peng et al. (2021), Liang and Xue (2009), Liang et al. (2010), and Session (2022) additionally defined constructs of end-user behaviorisms that defined security orchestration and self-efficacy. Halper (2020), Xiao et al. (2022), and Witanto et al. (2022) also found substantial evidence for the indoctrination of ZTA controls and frameworks aligned to negate dynamic threat variables systemic to operationalizing the TTAT constructs of effectiveness, cost, and self-efficacy; however, none of the researchers attributed a global catastrophe and subjective shift in workforce parameters as key constructs to a global comprehensive shift on deploying existing frameworks and technologies that were non-dependent of TTAT constructs. In addition to, Peng et al. (2021), Liang and Xue (2009), Liang et al. (2010), and Session (2022) defined constructs of end-user behaviorisms that coaligned user resistance to such complexities; however, users under scrutiny of the decentralized workforce and infrastructure, coaligned global regulatory influence, and dynamic increase in viable threats were not explicitly defined or substantiated in the research of Liang and Xue (2009), Liang et al. (2010), Peng et al. (2021), Session (2022), and Taherdoost (2022).

RESULTS

Key findings emerge from the short review above and a full exploration of the literature. As a result of numerous global events with a specific concentration on the COVID-19 pandemic, the increase of remote utilities has led to a surge in threat actors attempting to exploit organizational assets for financial or reputational gain. These incidents have had damaging effects on network connectivity, eroded reputational advantages, and progressed into a pivotal focal point in the realm of cybersecurity. The intensified need for effective and proactive threat mitigation and defense strategies across enterprise, industrial control, and operational technology-oriented platforms increased quickly during the pandemic (Halper, 2020). However, the traditional conservative approach, which relies on reactive technologies and defense mechanisms, cannot predict or eliminate threats by implementing appropriate cybersecurity principles. Understanding the cost of infrastructure and global demands that have been reshaped and reinforced in response to targeted threats finds a benefit to adding a new construct to the TTAT framework to allow flexibility. The study addressed a gap in literature, observing research gaps that fail to address how global events impacted the price and structural philosophy of incorporating micro-segmentation technology.

CONCLUSION

In conclusion, further research is needed to define the TTAT model more flexibly to provide a more inclusive instrument that details and includes the organization and user perspective when faced with an unplanned environmental event that can lead to a shift in commonly understood principles of function and dysfunction that can lead to an enhanced organizational plan of threat avoidance behavior when there an environmental shift that must be addressed in a rapid and streamlined manner. As the limitations of this article stem from a lack of quantitative analysis, the key findings are the first step in the introspective understanding that the TTAT framework can be posed to include unplanned event strategies. The TTAT framework can be modified to include a measurement that looks at the strategic introduction and motivation of technology usage coupled with event modeling and control frameworks that can directly impact and shape user behavior based on a specific critical event.

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Leveraging DEI as a Defensive Strategy in Cyber Intelligence and Security

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ABSTRACT

The cyber intelligence and security sector faces a growing number of threats and attacks that are increasing in complexity, but reports indicate that the current workforce lacks the qualified professionals needed to combat them. The U.S. Government and the educational community have been increasing efforts to help grow and diversify a workforce that continues to be primarily white male dominated. However, there are organization-level tactics that can also be leveraged to increase and enhance the talent pool. Diversity, equity, and inclusion (DEI) initiates should be viewed, not only as opportunities to engender equality, but also as an opportunity to help recruit and develop the talent pool necessary to strategically heighten cyber intelligence and security capabilities. Consequently, I will review the literature on the benefits that DEI can bring to cybersecurity. I will also discuss how we can move forward with DEI changes needed to support the industry's growing challenges. DEI should be considered part of a strategic defense against cybersecurity threats so I will also provide practical recommendations for leveraging effective DEI initiatives as a strategy to help build the force necessary to combat the increasing number and complexity of cybersecurity threats.

Keywords: cybersecurity, cyber intelligence, diversity, DEI, cyber-threats, inclusion, equity

INTRODUCTION

The cyber intelligence and security sector, which I will refer to in this paper as simply cybersecurity, faces an alarming workforce shortage. The Homeland Security Subcommittee of Cybersecurity and Infrastructure Protection (2023), Director of National Intelligence (2023), and the White House National Cyber Director (2023) along with private sector cybersecurity organizations all point to a severe lack of qualified talent needed to fill vacancies in the industry. The Office of the National Cyber Director (2023) estimated the difference between global demand and qualified cyber intelligence and security workers at approximately 3.4 million.

The lack of qualified professionals in this sector has some negative implications for industry and the nation's overall security. Cybercrime and criminals are more diverse than ever and so are their opportunities to breach the security of individuals, organizations and national governments. The Office of the Director of National Intelligence (2023) Annual Threat Assessment of the U.S. Intelligence Community indicates “Globally, foreign states’ malicious use of digital information and communication technologies will become more pervasive, automated, targeted, and complex during the next few years, further threatening to distort publicly available information and probably will outpace efforts to protect digital freedoms” (p. 27). Security leaders are reporting an increase in novel attack strategies such as data poisoning and the use of generative artificial intelligence (AI) to develop malware and create more sophisticated phishing messages (Pratt, 2023).

A trained cybersecurity workforce that is creative and divergent in their thinking is necessary to protect us from an increasing number of cyberthreats. Unfortunately, the technology industry overall has a reputation for lacking workforce diversity and the cybersecurity workforce is particularly homogenous. The World Economic Forum (2021) reported that the cybersecurity workforce is comprised of an estimated 9% Black, 4% Hispanic 8% Asian and about 24% female professionals. Zippia (2023) reported that as of 2021, 78.5% of cyber analysts were male, 60% are over 40 years of age with only 11% between 20-30 years of age, and approximately 8.59% are members of the LGBT community. These statistics have changed very little over the past 13 years.

While Artificial intelligence (AI) systems can be trained to detect some cybersecurity threats to help alleviate the workforce shortage, there are some limitations. Because threats, such as viruses and malware are constantly being changed by cyber criminals, AI systems require human experts who are creative in their approach to programming to combat them (Ansari et al., 2022). In addition, as cyber criminals become more advanced, existing AI data encryption protocols become easier for them to reverse-engineer, posing additional threats to data security (Ansari et al., 2022).

Government and industry officials point to education and DEI initiatives as critical components of a solution to the talent shortage in the cybersecurity sector. We should understand that DEI initiatives can, not only, increase the numbers of cyber professionals, but improve their capabilities to defend us against increasing cyber threats. A sustainable solution can only come from a multi-pronged approach that includes implementing or re-tooling diversity, equity, and inclusion (DEI) efforts.

REVIEW OF LITERATURE

The Efficacy of Current DEI Initiatives

Generally, there is no standard definition or understanding of workplace diversity nor are there many clear indications of what comprises an effective organizational DEI strategy. Consequently, it isn't surprising that the implementation of DEI policies and mandated diversity training are failing to drive real change and, in some cases, have increased employee biases and decreased feelings of belonging (Georgean & Rattan, 2022). In a recent survey of almost 6,000 workers, only about 30% of respondents placed much importance on diversity in their workplace, but most employees reported some DEI initiatives in place that consisted primarily of organizational policies to ensure fairness coupled with required diversity trainings (Minkin, 2023).

Diversity Training, often provided by outside consultants, is typically the cornerstone of most organizations' DEI programs. Unfortunately, it appears to be one of the least effective methods used to moderate workplace bias and increase managerial diversity (Chang et al., 2019; Dobbin & Kalev, 2018; Kalev et al., 2006). In fact, research shows that not only does mandate diversity training generally not result in any long-term positive effects, but it can also actually do harm by activating bias and decreasing feelings of inclusion for underrepresented groups. When opinions and behaviors are perceived as being mandated, employees will tend to resist. Sanchez and Medkik (2004) found that diversity training actually increased unfriendly treatment of non-white employees.

Organizational goals for the hiring, compensation, advancement and retention of underrepresented groups that include timetables for achievement. Dobbin and Kalev (2018) reported that while there is inconclusive evidence of the benefit of affirmative action's plans, specific organizational goals for hiring quotas can have positive results (Holzer & Neumark, 2000). Dobbin and Kalev (2022) indicate that many firms may lack accountability and transparency when reporting information to the public and may not take the goals into account when downsizing (Dobbin & Kalev, 2022). Dobbin and Kalev (2022) also indicate that measurements of systemic bias are largely absent from the literature.

If most cybersecurity organizations are relying solely on the components of mandated diversity training and organizational goal setting to augment any written diversity policy, it is easy to see why we haven't seen significant changes in workforce diversity in this sector. A discussion of benefits beyond racial and gender equality follows, which is particularly beneficial to cybersecurity teams and should highlight the need for strategic DEI initiatives for every organization.

DEI Benefits for Cybersecurity

Beyond the obvious benefit of expanding the sheer numbers of individuals to fill the cybersecurity talent gap and ensuring equity and fairness in the workplace, a review of the literature also indicates several organization-level benefits to implementing or improving workplace DEI initiatives. There appears to be an overall lack of understanding of the importance of DEI and the potential benefits that it can bring. The common focus of DEI is on preventing discrimination in the employment process and the elimination of social exclusion, which are very important. However, DEI isn't solely related to addressing disparities in the treatment of underrepresented individuals. There are additional potential benefits for every employee that can be particularly beneficial to the cybersecurity community. For example, the complex-problem solving, critical thinking, and divergent thinking skills that are needed to combat increasingly diverse cybersecurity threats, have all been shown to be positively influenced by DEI.

Critical Thinking is a multi-dimensional construct that involves the understanding and evaluation of information to make reasoned decisions. Bensley and Murtagh (2011) added that critical thinking involves a tendency to be open-minded and fair, yet skeptical in evaluating claims. Higgins (2014) discussed the importance of developing the quality of judgement and the ability to utilize skills and knowledge to resolve challenges and problems, particularly in the digital age when we are faced with such a tremendous scale of available information. Also, when considering the nature of cyber-crime, the ability of cybersecurity professionals to evaluate and interpret available information to formulate judgments becomes a critical skill.

Research indicates that there are cultural differences in critical thinking styles and performance (Lu, 2021; Lun et al., 2010) and that exposure to cultural diversity may enrich critical thinking skills (Inoue, 2005). However, in Loes et al.'s (2012) study, the only significant cognitive effects uncovered were related to actual interactions with diverse groups as opposed to mere exposures to diverse experiences. This is supported by Roksa et al.'s (2017) research, which found no differences in the development of critical thinking skills based on exposure to positive diversity experiences.

While much of the research around diversity and critical thinking is based on exposure to positive experiences, Roksa et al.'s (2017) research did indicate a significant negative effect of negative diversity experiences on critical thinking outcomes. Consequently, cybersecurity leadership should understand that negative diversity experiences, such as prejudice and discrimination, can negatively impact important critical thinking skills.

Creative Thinking. Exposure to diverse multicultural experiences has been found to heighten creative thinking (Storme et al., 2016). However, the research on team diversity shows mixed results. A seminal meta-analysis of research on creativity and innovation indicates that diversity related to specific job-level attributes showed a positive effect on individual and team innovation, but background diversity (i.e. race, gender, and age) showed a slight negative influence on innovation (Hülsheger et al., 2009). The reason for the contrast may lie in the idea that diverse teams may have difficulty communicating or reaching consensus when it comes time for decision-making (Dayan et al., 2017).

The reason for difficulty in decision-making for diverse teams can likely be attributed to divergent thinking. Homogenous teams tend to have convergent thinking, which makes decision-making easier. However, innovation and creativity call for thinking that diverges from the norm. The research on creativity and innovation highlights the idea that diversity should not be considered as a stand-alone objective, but rather as an important piece of a strategic DEI initiative.

Divergent Thinking. While homogenous teams may have increased cohesiveness, they often result in convergent thinking and uniformity in points of views, commonly referred to as groupthink. Groups that are made up of individuals with similar characteristics and backgrounds can tend to think alike and avoid dissenting from the opinions of the group. Apfelbaum et al. (2014) found that study participants assigned to homogenous groups were also much more likely to exhibit a self-serving bias in decision-making.

While similarity and conformity in thinking is beneficial for group cohesion, it can result in poor decision-making. Cybersecurity teams, which overall tend to be fairly homogenous in their makeup, cyber leaders should be aware of the dangers that it may pose to decision-making. In addition, in order to respond to and mitigate increasingly innovative threats, cybersecurity teams will need to develop more creative and innovative approaches. Empirical research on creativity and innovation highlights the need for divergent thinking (Clapham, 2010).

Complex Problem-solving. Interestingly, research has shown that diversity has a positive effect on complex problem-solving (Reynolds & Lewis, 2017; Hong & Page, 2004). Hong and Page (2004) found that identity-diverse teams of problem-solvers selected at random outperform homogeneous teams of hand-selected top-performers. The researchers attribute this to groupthink. As the team of hand-selected top performers becomes larger, their tendency to become similar in their approach to problem-solving becomes similar. Reynolds and Lewis (2017) attribute the increase in complex problem-solving not necessarily to gender, age or ethnic differences, but to diversity in perspectives and information processing styles.

Staying a step ahead of identity thieves, computer hackers, ransomware, malware, supply chain attacks, and denial of service attacks while identifying and mitigating critical vulnerabilities requires cybersecurity professionals to have complex problem-solving skills. In addition to preventing cyber-attacks, problem-solving skills will be especially critical for reducing downtime and losses in the event of a cyber incident. Fortunately, DEI has been shown to strengthen problem-solving skills.

Practical Suggestions for Cybersecurity DEI Initiatives

First, understand that diversity, equity, and inclusion are 3 separate and distinct constructs. Focusing on only the diversity portion of DEI may increase the cybersecurity talent pool but will not allow us to build highly function teams. We have evidence that supports the positive effect of DEI on critical thinking, innovation, creativity, and complex problem-solving. Consequently, cybersecurity leaders will need to think about each individually, but also create a comprehensive strategy that considers each separate construct.

DEI Leadership. Cybersecurity leaders are responsible for cultivating and modeling organizational culture. Creating a workplace environment with diverse, inclusive, and equitable hiring, compensation, evaluation, and promotion practices will take a genuine and organization-wide effort. DEI initiatives should be framed as a need for unique contributions, rather than a business asset. Research suggests that listing diversity as an organizational value, without additional justification was preferred by employees in underrepresented groups (Georgean & Rattan, 2022). Consequently, to eliminate potential pushbacks, it is beneficial to invite input and feedback from all levels when developing your organizational DEI strategy.

- A written policy is not enough to create culture of DEI.
- Focus and communicate the value of DEI for unique contributions.
- Walk the talk. Employees will look to you as a model of appropriate behavior.
- Elicit input and feedback from stakeholders to create a comprehensive DEI strategy.

Diversity. Cybersecurity leaders should focus on and promote the unique contributions that a diverse workforce can bring to the organization. Dwertmann et al. (2016) proposed that viewing DEI from the perspective of embracing and integrating the exchange of diverse ideas and information can only happen through what they term the synergy perspective, which reflects an organization-wide interest in the performance benefits of a diverse workforce. Diversity isn't just about race. It refers to embracing and celebrating differences in all individuals, regardless of religious beliefs, gender identity, appearance, cultural upbringing, socio-economic status, etc.

- Consider employee-led training or making diversity training optional.
- Work with stakeholders to create achievable goals for diversity.
- Create appropriate metrics for measuring progress toward DEI goals.

Equity. The equity portion of DEI is frequently equated with equality for underrepresented employees, which ensures that all employees are provided with equal opportunities and resources. However, equity relates to the potential allocation of additional resources and support necessary to ensure equal outcomes for everyone.

- Develop opportunities for mentoring and coaching.
- Implement a Blinded Promotion Review (Enders et al., 2020).
- Review current hiring practices for potential unconscious bias.
- Consider re-skilling and up-skilling underrepresented employees.

Inclusion. Elicit input and feedback from all levels to develop policies, performance metrics, and training efforts. Consider that bias cannot be eliminated through workplace diversity training. What has been shown to work to reduce bias is an increase in interactions among diverse employees.

- Create diverse teams to increase employee interactions.
- Avoid justifications for your DEI initiatives that focus on profitability.
- Work to build trust among diverse team members.
- Have a zero-tolerance for discrimination of any kind.
- Train managers to identify and squash veiled discrimination.

CONCLUSION

Cybersecurity leaders should view DEI as a moral obligation, but also as an obligation to their workforce and those who they work to protect from cyber-criminals.

Research indicates that we can leverage DEI initiatives to increase critical thinking, complex problem-solving, and creativity in the cybersecurity workforce to help innovate approaches to understanding vulnerabilities and develop increased cyber defense capabilities. While I have not provided a comprehensive plan to implementing a successful DEI strategic initiative, I have provided some useful suggestions that are supported by research that can be used to help develop a DEI strategy that can help develop a diverse and high-performing cybersecurity workforce.

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Graduate Student Investigator: Best Practices for Human Research Protections within Online Graduate Research

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ABSTRACT

This paper presents the best practices used by institutional review boards (IRBs) and human research protections programs (HRPPs) to prepare online graduate student investigators for human research protections specific to research within online graduate degree programs or where research supervisors are not proximal to graduate student investigators and their research protocols. In recent years, advances in artificial intelligence (AI), machine learning (ML), and other data mining/scraping forms have adversely impacted individual privacy and the unintended sharing of personally identifiable information (PII). With this growth of ubiquitous digital technologies, such as AI, ML, and data mining/scraping, used across online graduate degree programs, specialized training and preparation are needed to best prepare graduate student researchers for human research protections involving data with PII. Implications for IRBs and HRPPs are also addressed in this rapidly evolving climate, with recommendations for the design of online graduate degree programs that include graduate research and the best strategies to prepare online graduate student investigators for human research protections.

Keywords: Human Research Protections, Institutional Review Boards, Graduate Research, Graduate Education, Human Research Protections Programs, Student Research, Ethics Training

INTRODUCTION

A graduate student's submission of their research to the institutional review board (IRB) or some form of a research ethics committee is often a rite of passage remembered long after the student has completed the graduate degree. The purpose of the IRB is to ensure the safety of human subjects involved in research, privacy, and confidentiality for human subjects identifiers, fairness and equity in research recruitment, and to ensure risks are minimized for all research involving human subjects and/or their data, and to make certain no physical or psychological harm comes to the research participants (Lewis & Throne, 2021). In short, graduate student researchers must be best prepared to follow the rules and regulations to ensure ethical and responsible graduate research is conducted. However, some graduate student researchers blamed their research supervisors or the institution for lacking confidence and preparedness (Ciampa & Wolfe, 2019). Other graduate student researchers shared concerns over the constraints on their research due to the IRB and called for reimagining ethical research preparation in graduate education (Slovin & Semenec, 2019).

While submission of the graduate research protocols to the IRB or other ethical review processes may often be seen as a critical milestone for graduate student researchers, some past scholarly researchers have noted the impediments that may be encountered in the submission of the research to the IRB (Lewis & Throne, 2021; Lynch & Kuntz, 2019; Slovin & Semenec, 2019). Some institutions maintain “normalized research” expectations that may lead to unintended obstacles for graduate student researchers designing research protocols that may deter from what may often be perceived as this normalized course of inquiry (Lynch & Kuntz, 2019, p. 12). For example, Lynn and Kurtz (2019) reported on past research that noted this positioning of the IRB or other academic review as the gatekeeper for traditional expectations had been found to lead graduate student researchers to employ research protocols to ensure such reviews are "without interrogation," thereby deviating from their initial inquiry intentions (p. 12). At the same time, others have referred to this normalized or traditional IRB journey as a “post-positivist” view to maintain a status quo in the expectations for graduate research (Slovin & Semenec, 2019, p. 15).

Yet, still, others have noted that some faculty researchers perceive the IRB as an unnecessary process and conduct research out of bounds even though they understand the IRB and their aims are consistent with a desire to advance knowledge while protecting human subjects from harm or risk (Reisig et al., 2022). Unfortunately, these intentional IRB boundary violations may be passed on within the mentoring process of graduate student researchers when the online graduate program does not provide an otherwise sound and adequate foundation for ethical preparations to ensure responsible research. In this context, responsible and ethical research requires the training of graduate student researchers to comply with the policies and expectations of the IRB and/or human research protections program (HRPP) or other ethical research review processes.

Concurrently, other past researchers have reported on graduate students' frustration over their unpreparedness when submitting their research protocols to the IRB (Ciampa & Wolfe, 2019). In a study of a Doctor of Education program, Ciampa and Wolfe (2019) noted that graduate students reported receiving no preparation for the intricacies of submission of their research to the IRB or an understanding of the expectations for data collection and analysis in their submissions. Graduate students shared these feelings of unpreparedness from designing their research to completing the IRB application, and thereby, risks in the submission of the IRB application were identified as they had little confidence in whether their research protocols would be accepted.

When graduate student researchers' preparation for ethical and responsible research and human subjects' protections is not addressed intentionally within the graduate program, the problems reported in the past scholarship for these students' experience may persist. However, with the emergent use of artificial intelligence (AI), machine learning (ML), and other ubiquitous technologies in graduate research, this preparation becomes even more essential to ensure the practice of ethical and responsible graduate research across disciplines. When well synthesized within the design of the graduate program, a research component that includes preparation and understanding of the ethical requirements of IRB research can best prepare graduate students to become post-graduate independent researchers. The purpose of this chapter is to present the latest trends and best practices for the design of online graduate degree programs that include graduate research and the best strategies to prepare student investigators for human research protections.

BACKGROUND

The purpose of the IRB, HRPP, and/or other research ethics review processes in graduate research is to protect research participants, and participant data, and prepare graduate student investigators for ethical and responsible research with human subjects and data with human subject identifiers. Many past researchers have reported on the experiences of stress and frustration from the perceived expectations and pressures surrounding graduate research, including the perceived burdens of the online graduate.

program's research ethics review process. For example, Eliasson and DeHart (2022) called for the need to consider student researcher trauma in addition to human subject's protections for research participants as a component of methodological training. If review procedures considered student investigator trauma as part of the IRB submission experience, the authors noted that the trauma experienced by researchers would be placed more at the forefront as "a key consideration among risks imposed by the research process" (p. 8).

The ever-evolving nature of digital data collection methods has further complicated the challenges for ethical research review within online graduate programs. As technology is used in all facets of individuals' lives, graduate students' ethical research should be cognizant that ethical research is not exclusionary to disciplines. As student researchers embark on their academic writing journey and develop their methodologies for conducting research, students often employ various forms of data collection. Methods include online surveys or interviews, recruitment via social networking platforms, web scraping, and semantic analysis, with the component of understanding human behavior in some facet. Behavioral data sets can be collected with the use of different mediums (IoT, social media, facial recognition, intelligent homes) amassed through methods akin to data classification, data mining, and pattern recognition and then patterned through AI and machine learning in which the output can be analyzed through many multi-disciplined theoretical lenses (psychology, economics, sociology) (Bhatia-Lin et al., 2019; Saura et al., 2021a; Saura et al., 2021b). A common theme set within the research on the privacy of data is the question of whom is considered the owner of user-generated content (UGC) or user-generated data (UGD) (Saura et al., 2021b). The question can be raised depending upon the collection method to whom behavioral data belongs. The data ownership, be it UGC or UGD, is sometimes elusive and needs ethical oversight and conceptual understanding by both graduate student researchers and their research supervisors.

For example, the Educational Goods Framework (Brighouse et al., 2018) provides a lens for how higher education institutions prioritize and consider values in preparing graduate students to engage in research ethically and responsibly. Such a framework may allow us to explore the knowledge, skills, attitudes, and dispositions institutions want graduate students to develop as they navigate their research roles. The framework may also allow us to explore what institutions value – in conjunction with or in contrast to the values associated with federal IRB policy – as graduate students develop into researchers. Educational goods, then, can be used as an evaluative framework for future research to discover how an institution's IRB policy impacts the educational goods of an institution's graduate student researchers, to discover what values about research are prioritized by an institution in the implementation of IRB, and to discover what values about research are not prioritized by an institution. Doing so may expand our knowledge about how IRB policy impacts graduate student researchers and potentially broaden the theoretical framework of educational goods (Hseih & Shannon, 2005). Primarily, this and other models' distributive value of adequacy may be important to focus on within the educational goods framework to ensure adequate preparation for new investigators. In an era where graduate student researchers, as well as their research supervisors, may view the IRB or other ethics review as "bureaucratic," it is also an era where ethics review is an essential institutional task to protect individual data privacy and reduce risks and harms to research participants (Brown, 2023, p. 161).

THE BELMONT REPORT AND DEVELOPING ETHICAL RESEARCHERS

The preparation of graduate student researchers by the HRPP, IRB review, and/or other ethical review process involves quintessential steps consistently across fields and disciplines to ensure human.

participants and their data are protected within the research process. In addition to the Common Rule[1] that mandates the U.S. federal regulations for human research protections, these steps are particularly guided by *The Belmont Report*[2]to ensure three ethical principles for research with human participants are upheld: Respect for Persons, Beneficence, and Justice. The *Belmont Report* was written by the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research (1979) following the National Research Act of 1974, which was charged to identify the basic ethical principles necessary to underlie the conduct of human subjects research (HSR) and to develop guidelines to ensure ethical and responsible research is conducted in accordance with the principles.

Of course, not all graduate student research is research subject to IRB or another ethical review. Per federal regulations, this research must meet the federal definition of research and involve HSR or data with PII (Pater et al., 2022). Graduate program leadership must first distinguish whether the graduate research project involves actual HSR, or the research expectations defined by federal regulations, such as PII, before incorporating the ethical aspects of graduate research training. These distinctions require careful consideration, especially within a contemporary landscape whereby “computational capacity has greatly increased in the last 20 years, but new capabilities in fields like AI and machine learning are changing the nature of research and leaving significant gaps in both ethical norms and oversight” (Pater et al., 2022, p. 1). These computational nuances must be closely considered in the design of the graduate research component to ensure appropriate ethical oversight and investigator training has been included within the graduate program to prepare ethical and responsible graduate student researchers best. These decisions can be complicated by the allowances for ubiquitous digital technologies within the graduate research component. They often must be considered from a current perspective as these methods may introduce increased harm/risk for PII. As Huh-Yoo and Rader (2020) stressed

> *"Being digital meant increasing possibilities of confidentiality breach, unintended collection of sensitive information, and unauthorized data reuse. Concurrently, interviewees found it difficult to pinpoint the direct harms of those risks. The ambiguous, messy, and situated contexts of digital research data did not fit neatly into current human subjects' research protection protocols" (p. 1).*

Thus, graduate program leadership must carefully consider how risk assessment will be evaluated when digital technologies are allowed within the graduate research component (Huh-Yoo & Rader, 2020). The next section, Ubiquitous Technologies and Data Ethics, provides more on this.

Preparation for online graduate students to submit their research protocols to the IRB or other ethical review processes is often considered as solely a process-oriented, documental preparation rather than securing the conceptual foundations needed to ensure ethical and responsible research. Reisig et al. (2022) called for educational departments and institutions to make more concerted efforts to ensure sound ethical practices and training are provided to faculty and students, especially surrounding data management techniques and data sources to properly store and secure data archives. The authors noted the prior research that has shown the following:

[1] The Common Rule [45 CFR 46] sets forth the basic policy requirements for the composition and function of the IRB, criteria for IRB approval, informed consent requirements, and definitions, which have been adopted by multiple federal agencies. In addition to the basic policy, additional protections for vulnerable populations are regulated.

[2] The full text of *The Belmont Report* and details related to the history of the Report is available from the U.S. Health and Human Services Office for Human Research Protections at https://www.hhs.gov/ohrp/regulations-and policy/belmont-report/read-the-belmont-report/index.html

> *"…it is critical that researchers are made aware of such services and that these data management methods meet the needs of faculty for their full potential to be realized (Whitmire, Boock, and Sutton 2015). Efforts to this end encourage an organizational culture rooted in academic integrity and proper research conduct" (pp. 10-11)*

Even when IRB or HRPP policies are established to ensure directives exist for human subject protection, adequate researcher ethical preparation is necessary for the risk of psychological and/or physical harm to be elevated (Reisig et al., 2022).

Specifically, the Belmont principle of *Justice* can prepare graduate student researchers to understand fairness, equity, and inclusion in human subjects' recruitment and data collection. As Friesen et al. (2022) noted, it is essential for IRBs to ensure investigators understand that the principles that protect human subjects from harm may also exclude certain populations from research. Assurances for diversity require intentional "context-specific analysis," especially when involving vulnerable populations within the research protocols (Friesen et al., 2022, p. 10). When graduate student researchers understand research is a social good and research participation is a benefit, risks may be mediated in this context, whereby research participation is also a benefit to participants, not only a risk. However, in the use of ubiquitous technologies for research purposes, this context must also be considered for gaps in ethical oversight in the use of data collection methods that did not exist when The Belmont Report and Common Rule were established (Friesen et al., 2021). Therefore, the balance between risks and benefits for vulnerable populations and other research participants must be further considered in the wake of the contemporary climate with these emerging technologies for research inclusion and participant awareness of PII gathered (Brown, 2023; Friesen et al., 2021; Friesen et al., 2022; Throne, 2022).

Further, Hite et al. (2022) called for intentionality in responsible conduct of research (RCR) efforts for research involving graduate student investigators. Ethical dilemmas should be posed to new investigators within an educational setting to elevate their ethical and responsible judgment as to what constitutes RCR in specific situations such as predatory authorship, IRB violations, and the degree to which ethical challenges can pose harm and risk to research participants (Hite et al., 2022). The authors suggested that these learning activities may best occur within the training setting, such as "infused throughout the university curriculum and supported at the programmatic, departmental, and college levels," to better prepare graduate student researchers prior to facing them within the field (Hite et al., 2022). For example, Stevens and Caskey (2022) suggested this can be accomplished through writing an IRB proposal as an authentic, mentored, and scaffolded assignment to introduce ethical research within graduate coursework. Similarly, Brown (2023) encouraged justice and other ethical principles to be embedded within the curriculum with assurances that ethical reviews are a necessary good for all involved in the research process or those who oversee the work of new investigators who may be novices to what constitutes ethical research practices. The authors concluded the following:

> *"Instead of considering ethics as a matter of litigation, libel, complaints, and tribunals, they must encourage and enable research ethics committees to become more supportive, developmental, and dynamic, as otherwise, the ethics approvals processes will fail to keep in step with the changing landscape of the social sciences research" (p. 163).*

UBIQUITOUS TECHNOLOGIES AND DATA ETHICS

Data ownership and across all facets of individuals' lives, graduate students' ethical research should be cognizant that ethical research is not exclusionary to disciplines. As student researchers embark on their academic writing journey and develop their methodologies for conducting research, students often employ various forms of data collection. Methods include online surveys or interviews, recruitment via social networking platforms, web scraping, and semantic analysis, with the component of understanding human behavior in some facet. Behavioral data sets can be collected with the use of different mediums (IoT, social media, facial recognition, intelligent homes) amassed through methods akin to data classification, data mining, and pattern recognition and then patterned through AI and machine learning in which the output can be analyzed through many multi-disciplined theoretical lenses (psychology, economics, sociology) (Bhatia-Lin et al., 2019; Saura et al., 2021a; Saura et al., 2021b). A common theme set within the research on the privacy of data is the question of who is considered the owner of user generated content (UGC) or user-generated data (UGD) (Saura et al., 2021b). The question can be raised depending upon the collection method to whom behavioral data belongs. Data ownership, be it UGC or UGD, is sometimes elusive and needs ethical oversight and conceptual understanding.

As many attempts to comprehend how AI, ML, data mining/scraping, and other ubiquitous technologies are changing a graduate student's everyday life, research using these data collection methods is also being conducted at a rapid pace. Graduate students are reaching to understand, learn, and contribute to the literature in the void of what technology will provide in the coming years in ubiquitous digital technologies, such as artificial intelligence, machine learning, and data mining. Ubiquitous technologies are no longer considered just an Information Technology issue in academic research; the question of how ethical computing in research is disseminated without the researcher having a clear understanding of the technology or how the data is accumulated or cleaned from datasets (Drolet et al., 2022). Researchers are grappling with the ethical effects of research and the complexity of utilization, repercussions, and the application process from an ethical perspective.

The Melo Report from the U.S. Department of Homeland Security in Science and Technology provided a set of guidelines and ethical principles for communication Technology Research; the proposed framework was developed by both organizational leaders, lawyers, and scholars across the internet and communication technology (ICT) field (U.S. Department of Homeland Security, Science, and Technology, Cyber Security Division [CSD], 2012). The Melo Report has built the ethical framework for ICT research on the Belmont Principals, including respect for human rights and privacy, the informed consent process, confidentiality and anonymity, minimization of harm and risks, and transparency and accountability. The Report was supported by both Association for Computing Machinery (ACM) and the Institute of Electrical and Electronics Engineers (IEEE) Computer Society; the Office for Human Research Protections (OHRP) did not explicitly state its support or opposition to the Menlo Report. The Menlo Report was focused on cybersecurity research ethics and did not directly relate to HSR, which falls under the purview of the OHRP (Fiske & Hauser, 2014). Although the ICT ethical framework has been frequently cited, it has yet to be considered current since 2012 (Finn & Shilton, 2023). Instead, the Report and framework can be found as Archived Content in the Cyber Security Division (CSD) of the U.S. Department of Homeland Security. To ensure that technology is used appropriately for research across various fields, including ICT research, it is crucial to have a review and a call to action that provides clear guidance for the current research landscape.

As institutions are not required to apply regulatory and federal compliance policies to research that is not federally funded or identified as human subject research, as such, there can be many research protocols that need to be submitted to IRB for protocol review (Hine, 2021). Investigators should not rely on an ethical board. However, the researcher should first conceptually explore the study to understand the ethical needs from the participant recruitment stage to reporting research outcomes. Ethical issues such as identification of the difference between public and private data are issues that Williams (2023) found to be in question from a student perspective. Williams's conceptual article compares public data in newspaper archives as public data to what society may now view within public social media sites. Postulating that if data were available in a private but accessible social media group, do the data remain private? Can the connection of public data in the public domain virtually differ from the relinquishment of the private element when the user provides the information with the understanding of joining and posting information within a social media group? The additional question of informed consent must also be addressed as to whether the social media user is aware of how personally identifiable information (PII) is to be gathered and analyzed. Simple practices like social media scraping for sentiment analysis can throttle the ether between public and private data; as Williams (2023) found, delineating between public and private data depends upon the student's university's ethical policies to define that gray area. As technology ethics are expanding in complexity and understanding, the loosely demarcated nature of what constitutes participant privacy expectations must be clearly defined.

Reshaping Online Graduate Research with the Use of Technology Ethics

Can a comprehensive IRB review and ethical oversight be fully realized if the student or the reviewer needs to have intimate knowledge of the research outcomes? One of the significant concerns in research is the training provided to graduate students, emphasizing their focus and development within their core discipline with an understanding of ethical guidelines when utilizing technology in research. Scientists are utilizing technology in most facets of their research, thinking about how technology is being integrated into personal and social research as well as the consequences of computing, application, theory, and implementation may have an impact beyond the creation of the research itself (Head, 2020). As ethics should not be applied explicitly to one discipline but all disciplines, the question of the student's exploration of the data with ethical insight is questioned during the ethics review. As graduate student researchers develop their research strategies and methodologies, they need to prioritize the privacy protection of the study's participants with consideration of digital methods. To achieve this, researchers should consider asking themselves context-specific digital privacy protection questions to ensure the due diligence of participant privacy. Examples of such questions can be simple and straightforward. More questions than answers persist:

- Can the retrieval of the data process be explained thoroughly, as well as the ethical reasoning for using the data?

- In a constantly connected and accessible virtual society, can graduate student researchers collect data ethically and responsibly from participants in familiar, explainable language as to what PII is to be collected?

The utilization of ubiquitous technology in research has brought about an elevated awareness of ethical considerations across various elements of research stemming from recruitment to the narration of research results. Most of the standard policies and procedures that researchers implement begin with using clearly defined, informed consent documents written in understandable language to convey transparency of research processes. Shulman et al. (2022) reported issues with communicating instructions and educating users to protect their data. Like an informed consent document used as a method to educate the user/research participant on the privacy of their data and how it will be used, Shulman et al. noted that when it comes to privacy policies, “users may skip or disregard the messages the notifications and warnings convey” (p. 5). However, it is the responsibility of the ethical graduate student investigator to explore how the methods that will be used to collect, analyze, disseminate, and store research data to provide the research participant with both education and respect in keeping the data collected private to the extent of the agreement written in the informed consent. As researchers use ubiquitous technology in research, governance depends on guidance. It should adhere to the guiding principles of an ethical review, which should entail the components of an understanding of the privacy protection methods the researcher will use to safeguard the data when and if the data will be used again, and then move beyond the ethical review guidelines and to educate users with their research through participant empowerment (Ben-Ari & Enosh, 2013). Until guidance and data protection legislation are enacted akin to the GDPR in the United States, the question of the misuse and privacy of data exists in the back of a research participant's mind.

As noted, an example of such guidance stemmed from The Melo Report, hosted and supported by the U.S. Department of Homeland Security in Science and Technology to provide guidelines and ethical principles for communication Technology Research. The proposed framework was developed by organizational leaders, lawyers, and scholars in the Information and Communication Technology (ICT) field (DHS, 2012). The Melo Report built the ethical framework for ICT research upon the Belmont Principals, including respect for human rights and privacy, the informed consent process, confidentiality and anonymity, minimization of harm and risks, and transparency and accountability. The Report was supported by both the Association for Computing Machinery (ACM) and the Institute of Electrical and Electronics Engineers (IEEE) Computer Society. In a reflection on why the Menlo report failed, Finn and Shilton (2023) stated the following:

> *In the case of the Menlo Report, the work of the report was shaped by forward- and backward-looking goals. The report authors had future researchers in mind, hoping to enable new forms of research through data sharing. But they were also concerned with repairing a record of past controversial research practices and resolving an uncertainty disrupting their field: whether to treat their research data as human subjects data (pp 2-3).*

It may have been for the repair of past research and the uncertainty of disruption that the Office for Human Research Protections (OHRP) did not explicitly state its support or opposition to the Menlo Report, or as other researchers suggest, the Menlo Report was focused on cybersecurity research ethics and did not directly relate to human subject research that falls under the purview of the OHRP (Fiske & Hauser, 2014). Although the ICT ethical framework has been frequently cited, it has yet to be considered current since 2012 (Finn & Shilton, 2023). Instead, the Report and framework can be found as archived content in the U.S. DHS government website's Cyber Security Division (CSD). Guidelines and frameworks are needed to guide students' progress, and just as technology is dynamic, ethical policies cannot remain static.

Finally, the General Data Protection Regulation (GDPR) enacted in 2018 by the European Union provides a uniform framework that offers consumers greater control over their PII and other data, fosters organizational accountability, and applies strict penalties for noncompliance (ICO, 2023; Fox et al., 2022). GDPR focuses on protecting consumer data privacy and is concerned with the organizational culmination of users' private data; the research purpose or context defines research provisions. Although GDPR is read as a policy with a penalty for organizational collection of private citizen data without the user's knowledge, researchers are polarized on the application of GDPR to research, stating policies are too broad or too strict surrounding the use of secondary data and global data sharing (Soini, 2020). However, the seven fundamental principles of the research under the GDPR include "lawfulness, fairness, and transparency; purpose limitation; data minimization; accuracy; storage limitation; integrity and confidentiality; and accountability," which are tantamount to the application of the Common Rule policies (ICO, 2023, para. 2). Therefore, the broad application in data collection needs further review and revised to follow a structure with more ethical oversight, accountability and consequences for researchers and organizations that do ethical harm.

Online Graduate Student Ethical Reflection

Suggestions for a path to encourage ethical research practice using ubiquitous technology begin with the online graduate student educational preparation. Training for HSR must cover technology and the ethics of using technology understandably and incorporate reflexivity to ensure ethics training is iterative across the graduate research process. Graduate students may desire to challenge the status quo of ethical review boards, or as Reisig et al. (2022) noted, even prompted by the research supervisor to do so and invite subject matter experts to the table to define and defend the ethics of the process with the use of technology. Students should merge disciplines and learn from each other in ethical computing practices. The defense of having an epistemic challenge in research and needing to understand the ethical ramifications with or without technology is no longer valid. With technological advancements, research in the computing field or integrated technology now requires a greater emphasis on ethical reflection than in previous decades. As ethical norms and guidelines tend to be broadly defined, they exist in academic research as community standards. However, educational institutions promote and educate in responsible research practices, whereby ethics is a shared responsibility (Head, 2020). With guidance from their graduate research supervisor and/or dissertation/thesis committee, the graduate student researcher must consider the methodology to ascertain the ethical risk versus the benefits of the research outcome and whether the IRB performs an ethical review of the study (Fiske & Hauser, 2014).

Thus, in situations where contextual factors and ethical dilemmas are present, it is vital for the graduate research advisor and/or dissertation/thesis committee members responsible for overseeing graduate students to acknowledge and address any potential technology ethics that the student may overlook. However, if the committee members lack existing ethical insight, there is a risk that issues related to researcher misconduct may arise later. For example, Throne (2022) highlighted Hosseini et al.'s (2022) recommendations for IRBs and HRPPs to establish research ethics and data use frameworks to minimize inherent data biases embedded within datasets and the sustained social reproduction in the use of such data. Therefore, graduate student researchers must be trained to understand these intrinsic biases from the concurrent use of archival data and not solely rely on others to identify these risks and biases. Further, research supervisors should proactively seek and acquire knowledge about ethical considerations in using technology, ensuring they can provide informed guidance and oversight to students conducting research in this domain.

By remaining current with the ever-evolving ethical practices and technological advancements, research supervisors and/or dissertation/thesis committee members can fulfill their roles effectively and contribute to maintaining ethical standards in research. As such, any graduate research ethics program should encompass the entire research process, starting from the conception of research and extending to the publication of findings or attainment of a degree. Specifically, the online graduate research preparation program should instill in newly established researchers the methods to compose research with ethical considerations, fostering a culture of ethical practice in the context and understanding of the non-proximal oversight by the graduate research supervisor and/or the IRB and ethics review of the research protocols. This includes promoting ethical awareness, education on ethical principles, and encouraging reflective practices. When a program can sustainably provide an ethical framework for graduate student research to build their future research agenda, the chances of ethical research, whether within or outside academic research, may prove ethical practices are sustained and prioritized throughout a post-graduate researcher's career.

RECOMMENDATIONS AND FUTURE RESEARCH

The chapter authors call for two key questions to be considered for future research:

1. Do graduate programs best prepare graduate students as post-graduate researchers ensuring that their preparation enables them to flourish as ethical and responsible independent researchers in both academic and professional contexts?
2. How important is it to incorporate specialized training related to ubiquitous digital technologies into online graduate programs so graduate student researchers can thrive as post-graduate ethical and responsible independent researchers?

Other researchers have also called for continued investigation into best practices and preparation for graduate student investigators to ensure they leave graduate institutions as independent ethical, and responsible researchers. Specifically, Reisig et al. (2022) called for continued examination of their IRB violations scale to improve self-reporting capabilities as additional protections from HSR harm and risk. Likewise, Hite et al. (2022) called for future research to explore how training and education for graduate student researchers can address RCR and mitigate unethical issues within a higher education setting. For digital data collection, Huh-Yoo and Rader (2020) stressed the need to examine further the likelihood of participant data risk/harm and the uncertain characteristics involved in ethical oversight of digital research, which remains largely unknown and under ongoing debate.

CONCLUSION

It is clear from past scholarship that academic institutions should promote and educate in responsible research practices and make ethics a shared responsibility across graduate programs and the institution's research community, which includes IRBs, HRPPs, and any other ethical review body. As such, any graduate research ethics program should instill in new investigators the ethics, principles, and methods appropriate to ensure ethical, responsible research is conducted within an ethical research culture fostered in partnership with the IRB, HRPP, or other ethics review. The online graduate program must consider whether the research component meets the definition of research subject to IRB or other ethical oversight and whether digital methods, such as AI, ML, and data mining/scraping, are allowed before which ethical research learning outcomes are to be included within the graduate curriculum. Thereafter, best practices will consist of authentic research projects mentored by a graduate research supervisor whereby ethical principles are embedded within the learning activities. These steps help to promote ethical and responsible research for graduate student investigators who will be best prepared for a contemporary evolving research climate and encourage ongoing reflective practices to sustain ethical research practices throughout a post-graduate researcher's career. Future research is needed to continue to examine best practices for online graduate research programs to ensure graduate student researchers flourish as post graduate ethical and responsible independent researchers.

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Attitudes, Trust and Intention to Adopt Artificial Intelligence: The Moderating Influence of Ethnicity

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ABSTRACT

This quantitative research study examined the moderating influence of ethnicity on the relationship between trust of AI developers, social influence, attitudes about using AI and the intention to adopt AI. The public has a general distrust of AI and its developers. However, as the technology industry comes under increased scrutiny for its lack of workforce diversity and evidence of potential bias in AI algorithms designed for decision-making increases, underrepresented groups may be particularly distrustful. Because stakeholder attitudes of AI are shaping the future of the sector, it is important to understand their perceptions and ultimately, their intentions to adopt AI technologies. The purpose of the study was to explore the moderating influence of ethnicity on the relationship between trust and the intention to adopt AI using moderated regression analysis (MRA). In a sample (n=306) of the general population with a basic understanding of AI, the results of the study found that the interaction between ethnicity trust in AI developers, attitude about AI, and social influence were all found to have a statistically significant influence on the intention to adopt AI technology.

Keywords:

INTRODUCTION

The term Artificial Intelligence (AI) was originally defined by Stanford Professor emeritus, John McCarthy in 1955as “the science and engineering of making intelligent machines” (cited in Manning, 2020, para. 2). In essence, AI is the ability of a machine to simulate human intelligence and judgement to make decisions, conclusions and recommendations and has infiltrated virtually every aspect of our lives. AI algorithms control lives in spheres ranging from healthcare, education, and transportation to recruitment, college admissions, and even the provision of loans (Pessach & Shmueli, 2023). It has also provoked fear and excitement among humanity by creating human-like machines (Bryson & Winfield, 2017).

AI can be extremely beneficial, decreasing error rates of repetitive tasks, decreasing the need for humans to be physically present in their workplaces, increasing the efficacy of healthcare, and can lead to efficiencies such as reduced time, equipment, travel, and monetary expenditures. However, AI involves risks and distractions that warrant attention (Zhang, 2021). Because AI algorithms can be responsible for such life-altering decisions, often without a great deal of transparency in how the decisions are made, there is a widespread fear and lack of trust in AI and its developers. A contributing factor is mounting evidence that AI can be inherently discriminatory in its decision-making (American Civil Liberties Union, 2021).

However, trust in artificial intelligence (AI) can vary based on any number of factors including ethnicity (Zhang, 2021). From a socioeconomic point of view, trust exists in AI systems to the degree that the AI developers act in accordance with what the AI system is intending to represent (Bedué & Fritzsche, 2021). The demographic variable of ethnicity has variation in attitudes of AI technology which can range from general application to specific AI applications. Twenty-five percent (25%) of individuals from the public had negative attitudes toward AI implementation (Gao, 2020). The ease and speed of any AI technology adaptation will be impacted by the attitudes toward conditions and timeliness (Venkatesh et al., 2003). For example, Venkatesh et al. (2003) found that attitudes are significantly affected when less experienced users consider AI as user-friendly and efficient, consequently influencing behavioral intention to adopt a technology.

While technologists and policymakers have started to discuss AI and the uses of machine learning with increasing frequency, these conversations have typically not included the input nor the consideration of public opinion (Horowitz & Kahn, 2021). This emphasizes the need for leaders to learn to make judgments and decisions regarding the implementation of AI to inspire public trust (Zhang & Lu, 2021). According to Gao (2020), approximately 46% of the general public do not trust the developers of AI. These actors design and program AI systems based on the data collected and analyzed from the public that interact with AI systems (Piorkowski et al., 2021). Unfortunately, that may be particularly true for underrepresented demographic groups. This research examined the moderating influence of ethnicity on the relationship between trust and variations in attitudes and the intention to adopt AI.

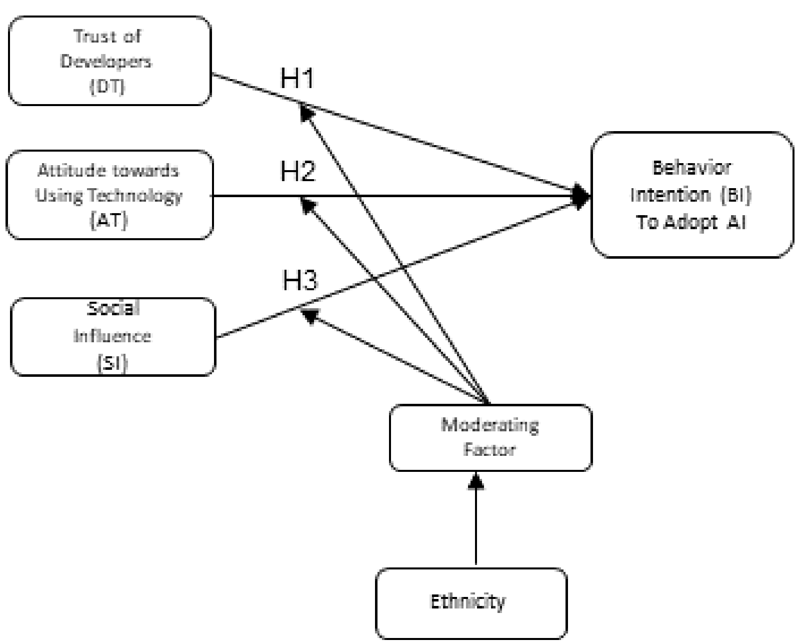
LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The general public's trust of AI has been shown to vary based on individual characteristics of the demographic subgroups (Zhang & Dafoe, 2019). In addition, research also reported that personalization algorithms of AI and facial recognition technology can result in negative outcomes for particular demographic groups, which will decrease the trust of AI in those subgroups of the general public (Zhang, 2021). The public's personal beliefs shape their attitudes, which can affect trust of AI (Zhang, 2021). Nevertheless, there is a great deal of potential for future research that expands on differences in trust and intention to adopt AI technologies (Zhang, 2021).

Recent research discusses the theory and development of AI systems and their escalating implications for human interchange and socioeconomic issues (Han et al., 2021; Ninness & Ninness, 2020). However, the degree to which AI can improve outcomes for certain demographic subgroups depends on the level of trust that potential users have. Zhang (2021) found that the lower socioeconomic class tend to have less trust in AI systems than other demographics. This lack of trust is due to less exposure to AI systems. Gefen et al. (2003) suggested that the degree and impact of trust changes with the level of experience with a technology. Additionally, it was found that the evaluation of AI-based services is driven to the degree of the perceived threat that AI poses to human uniqueness (Han et al., 2021).

The public's understanding and acceptance of AI may be related to education-level or socioeconomic status (de Vries et al., 2021). For this reason, the ability to generalize the findings in this research might be limited. Taken together, the more potentially disruptive the AI scenario (i.e., less human involvement), the lower the level of approval. This is to be expected with the sector entering an exciting but uncertain phase of AI development. However, we should consider them to be steppingstones to a bolder use of AI with potentially more ethical and inclusive service gains that will build trust in the technologies of the future.

Figure 1. *Theoretical Research Model*



Trust and Intention to Adopt AI

Research demonstrates that the public had a consensus that AI was trustworthy when used by institutions (Ryan & Stahl, 2020). The institution is expected to accomplish objectives because they are competent and possess values and aims consistent with those of the group (Thiebes et al., 2021). This means the public trusts that these institutions' goals are the same as theirs. However, Araujo (2020) found that the public had various levels of trust in developers who build AI systems, and this trust depended on multiple factors. Information on precise solutions that explain the contentious dynamic between government organizations and technology companies assisted organizations in building trust in the AI that is offered to the public (Zhang, 2021). This research maintained how perceptions associated with AI were influenced by several factors such as demographics and ethnicity (Araujo, 2020).

Generally, anything that is trusted needs to be worthy of that trust, also called trustworthy (Ryan, 2020). For AI technologies to be trustworthy, they must display the characteristics of accuracy, interpretability, and the ability to be explained (Kaur et al., 2022). AI should be robust, reliable, safe, support privacy, and security or resilience to attacks and ensure the mitigation of bias (Kaur et al., 2022). Choudhury et al. (2022) found that 'Trust' was found to mediate the relationship of 'expectancy' and 'perceived risk' with the 'intent to use AI.' The research's findings established conduits for future research and have implications on factors influencing intention to use AI (Choudhury et al., 2022). Moreover, it is vital to understand factors influencing individual's intention to use AI as initial intentions to use a system decides subsequent use (Snead & Harrell, 1994), and various seminal psychology-based research publications also support this association between behavioral intentions and ensuing behavior (Behringer & Sassenberg, 2015; Davis et al., 1989).

In order for AI developers to earn trust that they are building AI conscientiously, there needs to be more past principles to focus on mechanisms for demonstrating responsible behavior (Brundage et al., 2020). Making and assessing verifiable claims, to which developers can be held accountable, is one crucial step in the direction of earning trust Views of trustworthiness impact AI, influencing a person's choice and behavior associated with the product or service (Toreini et al., 2020). Lokey (2021) found that trust is an important predictor of the willingness to adopt a range of AI systems. Given the fundamental role of trust, there a strong practical need exists to recognize what facilitates and influences trust in AI, with numerous recent calls for research from industry (Shahriari & Shahriari, 2017), policymakers (Floridi, 2019), and scholars (Ribeiro et al., 2016). Ensuring trustworthiness of current and future practices of developers is a current emphasis in an area that reflects on appreciation that maintaining trust in AI may be critical to ensure acceptance and successful adoption of AI-driven products and services (Mayer et al., 1995; Siau & Wang, 2018). Research says how trust is established, eroded, or maintained depends on multiple factors, including a group's or individual's interaction with others, services, data, environments, factors, and products, which combine to form an individual's view of trustworthiness otherwise. Researchers' practical implications and conclusions emphasize that AI is here to stay, and these applications will become more and more prevalent (Horowitz & Kahn, 2021). With this in mind, building trust in these technologies is crucial for acceptance by all demographic groups.

Trust in the Developers of AI

Research shows that the public has varying levels of trust in actors who build AI systems (Zhang & Dafoe, 2019). There is concern over the absence of accountability by technology companies that operate AI-based social media platforms, but there is disagreement over the appropriate policy solutions. The Pew Research Center indicated that approximately 51% of the U.S. public feels that technology companies should be regulated beyond the level they presently are (Auxier, 2020). Simultaneously, Americans indicate that they have greater trust in public-sector technology companies than in the U.S. federal government to oversee the development and use of AI (Auxier, 2020).

Trust in the functioning of bureaucratic sanctions and safeguards of a system, especially the legal system, is the basis for institutional trust or trust of developers of AI (Lewis & Weigert, 1985). There is a concerning gap in accountability, given that governments and other organizations are turning to third-party vendors and their developers more often to provide AI-based applications for public services (Crawford & Schultz, 2019). Nevertheless, when confronted, many institutional actors attempt to disavow any knowledge, understanding, or explanation to remedy problems created by AI systems that they have procured from third parties. The institutions say that they cannot take responsibility for something they do not understand (Crawford & Schultz, 2019). Beneficial applications are more likely to be achieved, and risks are more likely to be evaded if AI developers earn the trust of a diverse society as opposed to presuming that there is trust (Brundage et al., 2020).

The general confusion and fear surrounding AI could undermine the technological institution's trust before implementation of any technology begins (Everett, 2017). Scholars have explored the normative implications of existing AI ethics guidelines, but no research has explored how cultural values are adopted by or influence AI policy (Ryan & Stahl, 2020). Toreini et al. (2020) mentioned that with that lack of reasearch there has been an increase in awareness of ethical dimensions of AI and is leading to a focus on ways of ensuring trustworthiness of current and future emplimentations of AI. The emphasis is due to the recognition that gaining and maintining of trustworthiness can be a key factor in ensuring acceptance and adoption of AI-driven services and products (Siau & Wang, 2018). Trust is often cited as a necessary fundamental property of the interface between any user and AI, but some research has shown that this has not been made clear in the learning models of AI (Jacovi et al., 2021). One of the focuses is on public trust, for which considerations of trust appear inadequate and exceedingly important for the reasons already expressed previously in this study (Knowles & Richards, 2021).

Hypothesis 1: Trust of developers in actors behind AI that is moderated by ethnicity has a significant influence on behavior intention to adopt AI.

AI has potentially extensive impacts on society, but this requires the public's trust from those who use the tools offered by institutions. Technology companies (institutions) and organizations will need to present AI in ways that build understanding and trust along with respect for human and civil rights (Bird, 2020). An accountable, transparent, fair, and regulated approach will be required (Bird, 2020). The research has found that Americans express a great deal or fair amount of confidence in the federal government at 26% compared to 41% in technology companies (Zhang & Dafoe, 2019). With these levels of trust from the public in these institutions, it is evident there is room for improvement.

Attitudes Toward AI

Previous research identifies how various subgroups view AI and denote the variations in attitudes (Zhang & Dafoe, 2019). Typically, research on AI and the variation in attitude is based on the correlation of individual knowledge and expertise of AI (Zhang, 2021). Ethnic group differences can influence an individual's attitude and drive the intention to use or interact with AI (Davis, 1989). A potentially related variable of socioeconomic status can also affect attitudes toward specific applications of AI, such as facial recognition technology (Zhang, 2021).

Research indicates that underrepresented groups in the U.S. are subjected to more bias in AI (Lee, 2018; Juhn et al., 2022). This creates a possible bias in the applied algorithms that are used to make decisions that can be discriminatory (Lee, 2018; Juhn et al., 2022). Evidence of the potential for bias in AI algorithms can influence the attitudes of underrepresented groups, who are subject to discrimination. There is also research that found some AI facial recognition systems to be discriminatory based on skin color (Hanley et al., 2021). As evidence of bias in algorithm programs and the potential for discriminatory decision-making in AI continues to mount, it can increase levels of general distrust and that may be particularly true in underrepresented groups.

One underlying trust issue stems from the fact that AI is programmed by a homogenous group of developers, predominately white males. After all, the technology industry overall continues to have a reputation for its stunning lack of diversity.

Consequently, homogeneity in programming AI to make decisions can lead to issues for individuals who belong to underrepresented groups. American Civil Liberties Union (ACLU) reports numerous examples of the discriminatory harms that can come to people of color, women or other marginalized groups due to bias in the data used to program AI (American Civil Liberties Union (2021).

Variations in attitudes toward AI can be conditioned by perceived security, reliability, and privacy concerns (Horowitz & Kahn, 2021). As attitudes improve about AI-enabled technology, the intention of the average individual to adopt the tools of AI will also improve. Other researchers developed a scale of general attitudes toward Artificial Intelligence (GAAIS). Schepman and Rodway's (2020) scale undertook its initial statistical validation through exploratory factor analysis that characterized negative and positive attitudes. These scales demonstrated good psychometric indicators and discriminant and convergent validity against current measures (Schepman & Rodway, 2020). The cross-validation of specific and general attitudinal instances of AI applications and summaries of tasks completed by specific applications of AI were obtained from newspaper articles (Schepman & Rodway, 2020). This survey data indicated that the public fostered mixed attitudes toward AI.

Variations in Attitudes Toward AI in Ethnic Subgroups

Other research showed that according to ethnicity, non-whites were less open to the use of AI than Whites (Antes et al., 2021). However, this could be partly due to the lack of familiarity with the technology (Antes et al., 2021). Jackson et al. (2008) found that although ethnicity differences in Internet access has dramatically decreased, Black adults still use the Internet and AI less intensely than other ethnic groups, even though access is not an issue. In addition, the gap between blacks and whites in traditional measures of internet, AI, and broadband adoption is more noticeable among certain demographic subgroups than among others (Smith, 2014). Specifically, African Americans in the older age group, as well as those who have not attended college, are significantly less likely to go online or to have broadband service in the home compared to whites with a comparable demographic profile (Smith, 2014).

Individuals surveyed living in East Asia were found to have greater trust in AI across several comparative surveys than in other regions. A survey conducted in 2019 with over 150,000 respondents in 142 countries found that 59% of those in East Asia showed that AI would mostly help society, while 11% indicated that AI would mostly harm society (Zhang & Dafoe, 2019). In comparison, in Latin America and the Caribbean, the region most wary of AI, 49% showed that this technology would help society, while 26% suggested it would mostly harm society (Neudert et al., 2020). Similar results have been reproduced in another regional survey showing East Asian countries viewed AI and its development and that of workplace automation most positively (Johnson & Tyson, 2020). Kelley et al. (2023) conducted a content analysis of open-ended responses and found that 14% of responses from South Korea described AI as worrying, compared with 31% in France and 30% in the United States. In the United States and the European Union, where trust in AI systems is mixed, there is widespread consensus that AI is a technology that should be carefully managed (Lee, 2018; Zhang & Dafoe, 2020).

Current research has concentrated on ethnic demographics related to fairness, bias, and the increasing number of decisions regarding the daily lives of human beings

(Pessach & Shmueli, 2023). More than knowledge and expertise, Zhang (2021) showed there are other correlates of attitudes toward AI that have been recently studied. Noted in his research was that those of lower socioeconomic status also tend to be less supportive of AI. These studies that identify how different demographic subgroups view AI show that the public is not uniform in their attitudes.

Hypothesis 2: Attitude on using technology that is moderated by ethnicity has a statistical significance on behavior intention to adopt AI.

Intahchomphoo & Gundersen (2020) indicated that AI can be the cause of unequal prospects for people from some ethnic groups. However, AI can aid in detecting ethnic discrimination, and AI can also be used in studying facial images and demographics of people from diverse ethnic backgrounds. The topic of AI and ethnicity can be deemed as a relatively new and emerging topic that needs more attention (Intahchomphoo & Gundersen, 2020).

Social Influence and Criticism of AI

The public tends to trust technology companies less if they have found a reason to criticize them often. Hitlin and Rainie's (2019) research found that users of Facebook were uncomfortable with how they were categorized on the platform. Twenty-seven percent of Facebook users maintained that the site's classifications do not accurately represent them (Hitlin & Rainie, 2019). Another example of the public criticizing technology is the case of a Google algorithm that classified people of color as gorillas (Lee, 2018). Another example is where an online photo-shopping application called FaceApp, was found to lighten the darker skin tones of African Americans because

European faces dominated the training data, and as a result, defined the standard of beauty for the algorithm (Cresci, 2017).

When the public is exposed to revelations of criticism, AI is viewed negatively (Cresci, 2017). Cass and Gull (1962) found in their research that certain criticism of AI was argumentative and controversial due to its criticism being based on philisophical methods. Garvey (2021) mentioned AI may rapidly become ubiquitous, corresponding with technological civilization itself. AI could become considered a necessity for modern times, similar to electricity or running water (Garvey, 2021). But this situation does not signify that all is well. Garvey's (2021) criticism is that while AI displays potential to empower and liberate users, support social institutions, improve wellbeing, and enable sustainable development, AI also threatens to automate and destabilize society, and degrade mental health of the public. Critics also imply that AI will enable the creation of superintelli-gent machines that herald the Apocalypse (Barrat, 2013; Bostrom, 2014; Cava, 2018; Clark, 2014; Müller, 2016; Russell, 2019; Yampolskiy, 2015).

Hypothesis 3: Social influence (SI), that is moderated by ethnicity has a statistical significance on behavior intention to adopt AI.

Arguably the seminal critic of AI was Mortimer Taube who was once a towering character in information and library sciences. Staub (1961), who was roundly criticized by the AI community when he published his criticism of the General Problem Solver (GPS), considered by many to be the second major AI program (Taube, 1961). Taube (1961) reviewed the literature on these so-called new data processing machines and considered the evidence for the machines whose inventers claimed can learn in just the same manner as a human, translate languages, make decisions, and carry out any intelligent operation that a human can. Taube (1961), who was considered a leading expert in the non-numerical uses of computers (anything other than numerical calculation at the time), including information retrieval and translation, referred to what AI proponents was doing as Fraud by computer.

METHOD, PROCEDURE, AND SAMPLE

This study used a quantitative survey design to explore the influence of ethnicity on the relationship between trust of AI system developers and attitudes concerning the technology. The statistical significance of AI trust and varying attitudes when AI is used by the general public, can assist institutions with understanding consumer distrust towards AI that is used for institutional products. As a result, institutions can build a strategy to modify the AI approach which will facilitate consumer attitudes and lead to more favor with trusting AI systems.

Research Design

Based on the review of literature, the demographic variable of ethnicity may influence relationships between trust in the developers of AI, attitudes about the technology, social influences and the behavioral intent to adopt AI technologies. This study empirically examined the main and moderating effects of ethnicity on these relationships and hypothesized positive moderating effects of ethnicity on these relationships. The survey questionnaire was prepared and hosted through the SurveyMonkey cloud-based platform. From a practical perspective, this study may be beneficial to the business community and provide leadership with information about the effects of ethnicity on adoption of AI systems as they may be offered to their internal or external customers.

LIMITATIONS

This research was limited in scope in various aspects. The featured study was not limited to a precise geographic area within the United States but was limited to individuals who reside in the United States. Self-reporting data collection was also a limitation. In addition, the total number of participants included in the study can also be viewed as a limitation and thus cannot be used to make inferences about the general population. A larger sample size would have provided additional statistical power to bolster and draw the conclusions from the various items dealt with in the demographics portion of the survey instrument. This study was also limited to the quantitative approach due to the instruments used.

Population and Sample

This study was approved by the Institutional Review Board of Saint Leo University. population for the study was the general public with a basic understanding of AI in the United States. Participants were recruited and collected through the SurveyMonkey platform. Target participants were from the general population of the United States who were least 18 years old. There were 306 survey participants. As indicated on Table 1, Five (0.02%) identified as American Indian or Alaskan Native, 37 (12%) identified as Asian/Pacific Islander, 20 (7%) identified as Black or African American, 28 (9%) identified as Hispanic, eight (3%) identified as multiple ethnicities, and 204 (68%) identified as White. Remaining participants did not respond. Results were grouped into a binary variable for identification (Table 2).

Table 1. *Demographic Data (n = 302).*

Demographic Variable	Frequency (n)	Percent (%)
Which ethnicity/ethnicity best describes You?		
American Indian or Alaskan Native	5	0.02
Asian/ Pacific Islander	37	0.12
Black or African American	20	0.07
Hispanic	28	0.09
Multiple Ethnicity	8	0.03
White/Caucasian	204	0.68

Table 2. *Demographic Variable for Identification (n = 302).*

Demographic Variable	Frequency (n)	Percent (%)
Which ethnicity/ethnicity best describes You?		
Non-White	98	0.32
White	208	0.68

. Instrumentation

The primary research instrument in this study is a multifactor survey questionnaire. The questionnaire was based on 16 questions based on a 7-point Likert scale. The survey was also used to collect demographic data of the participants. Additionally, the survey included questions pertaining to how performance expectations, effort expectancy, social influence, and self-efficacy effects the general public's trust of developers behind AI and attitudes on AI. All variables were used to determine statistical significance concerning the general public's trust with trust of developers behind AI and variations in attitudes.

The survey used an adaptation of the General Trust Scale developed by Yamagishi and Yamagishi (1994). This 7-point Likert scale (numbering -3 to 3) contains 17 items indicating the extent of agreement or disagreement with questions related to trust (Yamagishi & Yamagishi, 1994). This scale can also be divided into three subscales (i.e., predictability, dependability, and faith). According to Montoro et al. (2014), the internal reliability of the General Trust Scale ranges from 0.70 to 0.78, and the scale has been utilized in multiple studies to demonstrate validity.

Survey questions from Venkatesh’s seminal article was also used to evaluate technology acceptance. The questions and scales have been validated through an empirical test on the original data to support UTAUT (Venkatesh et al., 2003). The reliability for the studies used $\alpha = 0.70$ or greater. Questions were designed to determine the level agreement or disagreement with each of the factors that are to be measured through a seven-point Likert Scale. An example of such a question is: "I like working with the systems that use AI." The choices are strongly agreed, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, or strongly disagree (Joshi et al., 2015). Answers were designated a numerical score to be evaluated at the completion of the questionnaire, with the higher the score denoting the greater agreement.

A pilot test for the survey was conducted on 72 participants, who were outlined as a subset of the population. The data was reviewed and prepared for a Confirmatory Factor Analysis (CFA). The CFA was conducted on the data obtained from the 72 completed surveys to assess construct validity. A bootstrapping technique was employed to simulate 250 and 600 participants. The Confirmatory Factor Analysis

(CFA) using the multi-data source of (N = 72, N = 250, N = 600) cases were tested. Results revealed that the overall fit of the seven-correlated factor model, on its test, was statistically significant and that indicated that the questionnaire could appropriately and adequately capture the factor constructs for the study.

The subsequent findings resulted from the analysis:

- The majority of the loading factors were greater than 0.7.
- The intercorrelation between factors was close to zero.
- One factor (Trust) had the lowest factor loading during the analysis. Three of the seven items with the highest factor loading will be used for the survey, the other factors will be discarded. One additional question was found to be inappropriate and removed for a total of 5 discarded questions.

Table 3. *Social influence (SI), Attitude (AT), Behavioral Intention (BI), and Trust (DT)*

Descriptive Statistic	n	mean	SD	median	skewness	kurtosis
Social Influence	306	4.46	1.28	4.5	-0.02	-0.09
In general, people I know like using systems supported by AI.	306	4.67	1.41	5	-0.37	-0.16
People at my job who use AI based systems have more prestige than those who do not.	306	4.26	1.51	4	-0.09	-0.03
Attitude	306	4.64	1.31	4.7	-0.41	0.19
Using AI systems is a good idea.	306	4.59	1.37	5	-0.56	0.1
Using AI systems makes work more interesting.	306	4.69	1.51	5	-0.44	-0.16
I like working with the systems that use AI.	306	4.65	1.49	5	-0.31	-0.19
Behavior Intention	306	4.50	1.76	4.3	-0.35	-0.78
I intend to use an AI assisted system in the next month.	306	4.40	1.82	4	-0.22	-0.95
I predict I will use an AI assisted system in the next month.	306	4.64	1.85	5	-0.43	-0.88
I plan to use an AI assisted system in the next month.	306	4.46	1.88	4	-0.32	-0.98
Trust	306	4.81	1.08	4.8	0.21	0.18
One has to be alert for companies that produce AI applications is likely to take advantage of you.	306	4.79	1.45	5	-0.25	-0.41
There are many companies that product AI applications that don’t do what they say.	306	4.97	1.34	5	-0.06	-0.55
I trust AI applications that I know more than ones I am not familiar with.	306	4.80	1.71	4	-0.55	-0.61
Whatever work I have to perform, I feel more secure when I work with AI application, I know well than one I do not.	306	4.67	1.62	5	-0.44	-0.31

Note. $N = 306$

The descriptive statistics (Table 3) represented the number (*N*), the mean (M) trust in AI, standard deviation (*SD*), the minimum amount of trust in AI, and the maximum amount of trust in AI. This quantitative study used a moderation regression analysis to examine the impact predictors of trust of developers, attitude towards using technology, and social influence. The results of this model can be analyzed to determine whether ethnicity, as a demographic variable, moderates the relationship between the independent and dependent variables.

RESULTS

A Pearson correlation analysis (Table 4) indicated significant positive associations between all predictor variables with the exception of ethnicity. Ethnicity showed an insignificant negative correlation to social influence, attitudes about AI, trust in AI developers and intent to adopt the technology. However, the interaction variables of ethnicity with social influence, attitude, and trust were all shown to be statistically significant at the .01 level.

Table 4. *Pearson correlations matrix of variables and interaction terms*

	Social Influence	Attitude	Trust	Ethnicity	Social Influence* Ethnicity	Attitude* Ethnicity	Trust*Ethnicity
Attitude	.697**						
Trust	.478**	.528**					
Ethnicity	-0.085	-0.094	-0.019				
Social Influence*Ethnicity	.669**	.460**	.336**	.657**			
Attitude*Ethnicity	.459**	.671**	.376**	.651**	.841**		
Trust*Ethnicity	.235**	.267**	.610**	.761**	.736**	.762**	
BI	.617**	.740**	.598**	-0.104	.390**	.493**	.307**

** Correlation is significant at the 0.01 level (2-tailed).

Model 1 includes the individual-level variables (ethnicity and trust of AI developers) and the interaction variable (ethnicity*trust). These variables are grouped to examine whether or not individual characteristics could influence behavioral intent to adopt AI. At the individual-level, Trust of AI developers was shown to be a significant predictor, p = .011 of intent to adopt AI when controlling for ethnicity. The individual-level ethnicity variable failed to reach significance p = .164. However, the interaction (ethnicity*trust) F (3, 302) = 57.27, p = .033, ΔR^2 = .356 was found to have a significant influence on Behavioral Intent to Adopt AI (BI).

Model 2 (Table 5) includes the individual-level variables (ethnicity and attitude toward AI) and the interaction variable (ethnicity*attitude). The individual-level ethnicity variable when controlling for attitude, failed to reach significance p = .058. However, the interaction between Ethnicity and Attitude about AI, which was shown to have a significant influence on Behavioral Intent to Adopt (BI) F (3, 302) = 126.05, p = .004, ΔR^2 = .554.

Model 3 (Table 5) includes the individual-level variables (ethnicity and social influence) and the interaction variable (ethnicity*social influence). Social influence was shown to be a significant predictor, *p* = .067 of intent to adopt AI when controlling for ethnicity. The individual-level ethnicity variable when controlling for social influence did reach significance *p* = .042. However, the interaction of Ethnicity* Social Influence *F* (3, 302) = 62.79, *p* = .118, ΔR^2 = .0380, which was not shown to be a statistically significant influence on Behavioral Intent to Adopt AI.

Table 5. Regression results with Interactions

Predictors							
	B	SE	*t*	ΔR^2	R^2 *Change*	F(df)	*p*
Model 1				0.356	0.01	57.27(3,302)	<.001
Constant	3.267	1.361	2.4				0.017
Trust in AI Developers	-1.985	0.778	-2.551				0.011
Ethnicity	0.383	0.275	1.395				0.164
Trust*Ethnicity	0.337	0.157	2.143				0.033
Model 2				0.554	0.012	126.06(3,302)	<.001
Constant	2.977	1.031	2.887				0.004
Attitude	-1.73	0.572	-3.027				0.003
Ethnicity	0.397	0.209	1.902				0.058
Attitude*Ethnicity	0.335	0.116	2.874				0.004
Model 3				0.38	0.005	62.79(3,302)	<.001
Constant	2.749	1.116	2.463				0.014
Social Influence	-1.16	0.632	-1.836				0.067
Ethnicity	0.479	0.234	2.046				0.042
Social Influence*Ethnicit	0.21	0.134	1.568				0.118

Note: Dependent variable = Behavioral Intent to Adopt AI (BI)

DISCUSSION, CONCLUSIONS AND RECOMENDATIONS

This study examined the influence of ethnicity on the relationship between trust, variation in attitudes and the intention to adopt Artificial Intelligence (AI). Understanding the influence of ethnicity on variations of attitudes towards AI and the public's trust of the designers of AI applications is a potentially critical advantage to AI developers and policymakers, as it may provide additional insight into how they might promote the acceptance of the technology (Horowitz & Kahn, 2021).

Leaders and organizations who have a better understanding of the moderating relationship or influence of ethnicity combined with knowledge about attitudes and about trust of developers of AI, social influence, and the behavioral intention to use AI could improve businesses and organizations design and decision-making effectiveness to support organizational success. Simply put, understanding what makes the customers in your market accept and use what you are selling helps organizations design what the customer will accept and buy going forward.

Previous studies focus primarily on beliefs from a demographic standpoint at individual level (Cheng et al., 2022; Zhang, 2021; Araujo, 2020; Auxier, 2020). The prior set of research was crucial for revealing those existing assumptions about politics and ethics shape attitudes. Additionally, the public's attitudes about AI can be affected by messaging. The research also found that Behavior Intention (BI) is significantly affected by SI, attitude toward AI (AT), and trust of developers of AI (DT), as evidenced in Table 4.

Considering the findings, business leaders and AI developers can consider that ethnicity significantly influences AI's trust. As trust decreases, the effect on this interaction is more significant in Whites than non-Whites. The implication indicates that as trust in the U.S. general population declines, the intention to adopt AI falls, but this relationship becomes more pronounced in whites than non-whites. What is also interesting is that there is not a significant relationship between trust and socioeconomic status, political affiliation, demographic, or the intention to adopt AI.

Another finding useful for business leaders and AI developers is that ethnicity significantly influences attitudes toward using technology. Furthermore, AI and the effect on this interaction are more significant in Whites than non-Whites. This indicates that as attitude toward using technology or AI in the general population decreases, intention to adopt AI decreases, and this relationship becomes more pronounced in Whites than non-Whites.

As technology business leaders and AI developers navigate business environments, it is often a complex and uncertain process (Kim & Lim, 2020). Sometimes leaders need available insights into potential customer interests' attitudes and a level of trust to make quality decisions to maximize organizational success. More recently, this complex and uncertain process has been increasingly exposed to the fears of potential customers in the news headlines and public discourse (Barrat, 2013). This discourse concerns introducing AI applications like Alexa, Siri, ChatGPT, and AlphaGo (Salles et al., 2020). These types of AI technologies present unique impediments and need to help executives better understand what could potentially hold back their introduction of AI applications (Chui et al., 2018).

Understanding what the public thinks about AI can help anticipate future contention and therefore attempt to predict consumer behavior (Zhang, 2021). This knowledge, paired with past experience and competence, can help formulate and apply better decision-making processes mentioned in recent research (Kozioł-Nadolna & Beyer, 2021). Understanding consumer attitudes will likely be helpful in how companies make decisions regarding AI in the years ahead. As AI evolves, there is a need for AI providers to be open to new ways to confront complex topics and be more efficient ways to do everyday things. The insights gleaned from this type of research highlight the significance of technology businesses focusing on the accuracy and trustworthiness of AI-generated content. When displaying accountable AI use and its capability to offer reliable information, companies can develop and preserve the consumer in a time that presents AI as a solution to their needs.

Recent survey research found that less than one-third of Americans thought that tech companies do what is right "most of the time" or "just about always;" moreover, more than half believe that tech companies have too much power and influence in the U.S. economy (Smith, 2018). In today’s business environment, trust should not be considered as just a public relations goal but a mission-critical goal. Research into the attitudes and trust in AI helps businesses provide explainability, therefore fostering more trust in the applications being presented to the public (Ferrario & Loi, 2022). Trust fosters positive attitudes about risk and improves opinions about its fairness and potential usefulness, leading to increased behavioral intention to adopt AI (Araujo, 2020).

This study found that the interaction of ethnicity and trust of developers of AI, attitude toward using technology, and social influence all have a statistically significant influence on behavior intention to adopt AI. Considering the findings, business leaders and AI developers can consider that ethnicity significantly influences trust in AI systems. As trust decreases, the effect on this interaction is more significant in Whites than non-Whites. This finding indicates that generally, as trust in the U.S. general population decreases, intention to adopt AI decreases, but this relationship becomes more pronounced in Whites than non-Whites.

Another finding useful for business leaders and AI developers to consider is that ethnicity significantly influences attitudes toward using technology. Furthermore, AI and the effect on this interaction are more significant in Whites than non-Whites. This finding indicates that as attitude toward using technology or AI in the general population decreases, intention to adopt AI decreases, and this relationship becomes more pronounced in Whites than non-Whites. Another point of interest is there is no significant relationship between trust and socioeconomic status, political affiliation, demographic, or intention to adopt AI. This relationship also has a positive coefficient.

IMPLICATIONS

Findings in this research reveal that trust of developers behind AI, attitudes towards using AI and social influence have a statistically significant relationship towards behavior intention to adopt AI. However, moderating variables of political affiliation and socioeconomic status does not have a statistical significance on behavior intention to adopt AI. Although ethnicity did not have statistical significance related to social influence, statistical significance was found in the relationship between trust, attitude, and the behavioral intention to adopt AI.

Implications for technology company developers and leaders is to design and develop AI applications with more diversity towards ethnic differences. The current method of AI development utilizes ethics as the basis and does not take into consideration the trust and attitudes caused by ethnicity. The implementation of diverse AI applications is multifaceted due to the extensive number of ethnicities in the general U.S. population. Each ethnicity has its own set of cultural norms which impacts attitudes and trust of behavioral intent. Embracing the addition of diversity in AI application design can assist leaders and developers with investing their efforts in the ever-varying development of AI systems. This insight helps leaders and developers in technology organizations tie the public's acceptance of AI to their decisions when introducing new and innovative products to the market.

Suggestions for Future Research

Even though this research examined trust in developers (actors) behind and attitudes towards AI systems based on ethnicity, revisiting this approach is warranted due to the evolving nature of politics and the economy (Zhang & Lu, 2021). The population sampled for this research focused on the general public in the United States due to time and cost considerations. Future research in this area could benefit from examining more than one country. Additionally, future research on regions that contain several countries utilizing theories involved in this study could yield new insights.

As more AI systems become deployed worldwide, the public will increasingly interact with AI applications online, in public, or at their workplaces (Zhang, 2021). Other research has found that there are other correlates of attitudes toward AI. Another avenue could include emerging AI applications such as chatbots. Zhang (2021) found that although computer scientists prefer to define AI without emphasizing comparisons with humans, popular understanding by the general public of the technology tends to anthropomorphize AI. The general public has historically described and conceived AI as characterized by human traits (Salles et al., 2020). AI-based applications such as Google Bard, ChatGPT, Chat Sonic, Bing Chat, and others are generative AI applications and can return human-like responses evoking the comparison to human traits.

Another direction of research in this area could be to focus on the demographic results of this study. Although this research did not specify specific targets for each ethnicity category, it could be illuminating to do so. One example would be to aim for participation from each ethnic background to mirror the current population percentage in the United States. The data collected should be approximately 14% of the population sample in the study.

CONCLUSION

The research study examined the influence of ethnicity on the public's trust of developers of AI systems, the variation of attitudes towards AI and social influence. The hope is that these findings would help to improve the approach of leaders and developers of AI systems companies approach the design of their products. This approach incorporates the public's input as a primary stakeholder in the design as opposed to organizations primarily using what is considered to be "ethical" to design an AI system. This study focused on adding to the body of literature the behavioral intention to accept AI which is part of technology acceptance. Hence, this research can be utilized by AI technology businesses to successfully plan implementation strategies for fielding AI-driven tools.

Findings of this quantitative cross-sectional research revealed a statistically significant relationship between behavioral intention and adoption of AI with trust, attitude, and social influence of the general U.S. population. Additionally, the moderating variable of ethnicity had a statistically significant relationship with trust and attitude on behavioral intention to adopt AI. The addition of diversity in the development and design of AI systems will transform AI by being inclusive of various cultural norms in the general U.S. population. Failure to include ethnicity and cultural norms in AI can lead to decreased use of the applications offered to the population, decreasing profits for technology companies.

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Data Ethics and Human Research Protections in the Evolving Spaces of Research with Ubiquitous Technologies

Robin Throne, Western Governors University

ABSTRACT

This paper presents an analysis of the continued trends in the shifting spaces surrounding research with ubiquitous technologies specific to the challenges this research raises for Institutional Review Boards (IRB) and Human Research Protection Programs (HRPP). The paper builds on two prior papers in 2022 and illustrates the ongoing need for IRB and HRPP professionals to consider protections of human subject data from a perspective of the Belmont Principles.

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Adverse Trends in Data Ethics: The AI Bill of Rights and Human Subjects Protections by Robin Throne https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4279922

Free the Data but Not the Human Subjects Identifiers by Robin Throne: SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4304179

Challenges Women Face While Balancing Professional and Maternal Jobs

Krista Troiani, Penn State University
Tina S. Krolikowski, Carlow University

ABSTRACT

Women face various challenges while maintaining simultaneous professional and maternal roles, which typical require coping strategies and support to achieve effectiveness within the workplace. Appropriate accommodations, support, and coping strategies relate to job satisfaction and the ability to work additional hours (Abendroth et al., 2012; Troiani, 2023). Previous qualitative research has identified various themes related to working professors' experiences with managing dual roles and has further suggested the inclusion of various accommodations and support within workplace settings (Troiani, 2023). The proposed research will provide quantitative support for organizational accommodations, coping strategies, support mechanisms, and challenges in relation to working mothers. The following research questions will be considered: (1) What is the perception of benefits through accommodations in enhancing organizational efficiency within an area of employment? (2) What coping strategies benefit working mothers? (3) What support mechanisms are available to working mothers? (4) What are the challenges working mothers face? The researchers will construct questions related to these questions and the factors identified in previous research (Troiani, 2023). Data collection will consist of electronic surveys distributed to working mothers within higher education settings. It is suspected that accommodations including management and flexibility will be reported by a majority of working mothers, and time management and self-care are expected to be the coping skills most commonly used by working mothers. Further, it is expected that working mothers will report that support from their partner, family, workplace, and community is vital to effectively maintaining dual roles. Lastly, it is expected that the most common challenges will consist of work-life balance, juggling dual roles, and physical and mental health. Practices must be developed and implemented to promote equality and adaption to the cultural, political, and organizational platforms of women within our economy. These practices should include flexibility, accommodations, and a healthy work environment that yields healthy work-life balance and increased organizational efficiency.

Ethical Marketing and the Effects on Consumer Behavior

Emily Dreyfus, Commonwealth University – Bloomsburg University

ABSTRACT

Ethical marketing is essential to a company because it presents core values, shows transparency, and, most importantly, builds consumer trust. Although unethical marketing practices can hurt a brand, businesses still use them. There is a gap in knowledge about unethical marketing practices, which are used to manipulate consumers and gain a competitive advantage in the marketplace. This presentation will present research into ethical marketing practices and how they should be used to encourage honesty and positively influence consumer behavior. This presentation seeks to address ethical marketing, provides a framework, and discusses unethical marketing practices, advertising, and marketing rules within the Federal Trade Commission. Two legal action suits will be presented involving unethical marketing campaigns and their adverse effects on consumer behavior. Additionally, this project will examine the impact unethical marketing has on consumer relationships with the brand.

Building Open Educational Practices (OEPs) and Open Educational Resources (OERs) for Social Justice & Equity in Higher Education

Caroline Fitzpatrick, Alvernia University

ABSTRACT

As our society continues to navigate out of the pandemic, there is no denying that the world has changed. Even higher education, a notoriously slow industry to adopt or adapt to change, was thrust into chaos and uncertainty by COVID-19's spread and its influence on daily life. The stakes are high as the decline in "the number of Americans going to college — down by nearly a million since the start of the pandemic, according to newly released figures, and by nearly three million over the last decade" due to high costs and the greater public skepticism of the need for a college degree (Marcus, para. 2-4, 2022).

The issue of affordability and access to quality educational materials in the form of Open Educational Resources is one strategy for addressing inequity and costs. The unfortunate truth is that more students aren't purchasing required textbooks. In the report Fixing the Broken Textbook Market (2014) by the Center for Public Interest, research indicates that two-thirds of surveyed students had chosen not to buy or rent some required course materials because they couldn't afford them. The study also states an effective alternative would be the use of more open resources and open educational practices (OEPs). "Free online, free to download, and affordable in print: open textbooks operate in the exact way student respondents felt would improve their performance in class. Not only are open textbooks more accessible, but they have the potential to save students $100… per course, per semester" (p. 13). According to Education Data (2022), 25% of students reported they worked extra hours to pay for their books and materials; 11% skipped meals to afford books and course materials (Hanson). OEP and OER opportunities (adoption or creation of free texts; affordability, retention) and the challenges (quality control, material adaptation time) will be discussed.

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Beyond Conventional: Pioneering AI-Driven Assessments in Higher Education

Melanie Wiscount, University of Illinois – Gies College of Business

ABSTRACT

The rapidly evolving landscape of innovative technology, particularly Artificial Intelligence (AI), presents an untapped reservoir of potential for higher education. Among the trailblazers in the AI arena is ChatGPT, not just a conversational AI, but a "Great Productivity Tool" poised to redefine assessments in academia. This presentation seeks to reveal a variety of ways ChatGPT can be creatively integrated into assessments.

In an era where real-world applicability and skills are paramount, traditional assessment methods often fall short in capturing authentic student capabilities or developing much-in-demand skills. ChatGPT, with its advanced language processing abilities, offers an interesting solution. From facilitating real-time Q&A sessions, aiding in complex problem-solving tasks, to simulating real-world scenarios for students to navigate and make recommendations, ChatGPT embodies the essence of authentic and active thinking assessment with inquiry-based learning.

Beyond mere assessment, the integration of ChatGPT into the academic framework serves a dual purpose. It not only augments the learning experience but also equips students with invaluable AI skills, an essential competency in today's digital age. As industries globally lean heavily on AI-driven solutions, preparing students with hands-on AI experience becomes not just an advantage, but a necessity.

In a quest to mold future-ready graduates, it is imperative for academia to evolve in tandem with today's technological advancements. This session beckons educators to explore the transformative potential of ChatGPT in shaping the next generation of assessments and, by extension, the next generation of industry-ready professionals.

Join me to lead the charge in this pedagogical revolution.

The Need for Remote Access Connectivity with ERPs

Jae Hoon Choi, North Carolina Agricultural and Technical State University

ABSTRACT

The COVID-19 pandemic has had a profound impact on the way businesses operate. One of the key changes is the need for Enterprise Resource Planning (ERP) systems that support remote work. With lockdowns and remote work, organizations had to rely on ERPs to maintain essential business functions without employees being present in the office. Consequently, ERPs became indispensable for ensuring the continuity of business functions with employees being dispersed and working from home.

Remote access has emerged as a mission-critical feature of ERPs. The ability for employees to securely access ERPs has become essential for business operations. This ensures that employees perform their roles effectively, access data, and collaborate with colleagues, regardless of their location.

SAP has been at the forefront of developing innovative solutions to address the changing business environments. One of the newest offerings from SAP is the Remote Access Connectivity (RAC) ERP built on cloud computing. This cloud-based approach enhances scalability and flexibility, allowing organizations to adapt quickly to changing circumstances. With the increasing importance of remote work, the ability to access critical business data and process remotely is a significant advantage. SAP RAC provides a solution which integrates cutting-edge technologies to empower businesses to operate efficiently, even when their workforces are dispersed.

The goal of this presentation is to add the existing body of literature regarding the need for RAC with ERPs. Additionally, this presentation provides detailed information regarding SAP RAC with practical implications for practitioners, faculty and organizations seeking to move to a remote ERP.

Data Governance Dilemmas: Healthcare in the Analytics Era

Yucheng Chen, Commonwealth University – Bloomsburg Campus
Gwendolyn Powell, Bloomsburg University ACE Program- North Pocono School District

ABSTRACT

Healthcare organizations are increasingly turning to data analytics to derive valuable insights, enhance patient care, and optimize operations. However, effective utilization of healthcare data and healthcare analytics hinges on robust data governance practices. Data governance in healthcare involves managing data quality, security, privacy, and compliance to ensure that data-driven decisions are both accurate and ethical. One of the foremost challenges in healthcare data governance is the sheer volume and diversity of data generated daily. Healthcare organizations accumulate vast amounts of structured and unstructured data from electronic health records, wearable devices, clinical trials, and more. Ensuring that this data is accurate, consistent, and up to date is a complex undertaking. Furthermore, data from disparate sources often lacks standardization, making integration and analysis challenging.

Another significant challenge in healthcare data governance is maintaining data security and patient privacy. The healthcare industry is a prime target for cyberattacks due to the high value of healthcare data on the black market. As a result, healthcare organizations must invest heavily in cybersecurity measures to protect patient information. Compliance with regulations like the Health Insurance Portability and Accountability Act (HIPAA) adds another layer of complexity to data governance. Healthcare organizations must strike a delicate balance between leveraging data for analytics and ensuring patient privacy and regulatory compliance.

Finally, the rapidly evolving nature of healthcare technologies and regulations poses an ongoing challenge for data governance in analytics. New devices, applications, and data sources continuously emerge in the healthcare landscape. Additionally, regulations governing data usage and privacy are subject to change. Keeping up with these developments and adjusting data governance practices accordingly is essential for healthcare organizations to harness the full potential of data analytics while mitigating risks. In summary, effective healthcare data governance in analytics demands addressing challenges related to data volume, security, privacy, and the dynamic healthcare environment. Overcoming these challenges is crucial for healthcare organizations to leverage data analytics for improved patient outcomes and operational efficiency.

Every Student Deserves a Gifted Education - 5 Shifts to Nurture Each Student's Unique Strengths, Passions, and Talents

Brian Butler, The Answer's in the Room Educational Consulting, BKB, LLC.

ABSTRACT

In gifted education, we've long been asking the wrong questions. Instead of asking, "How can we increase diversity in Gifted Programs?" We should be asking, "How do we create the conditions, expectations, beliefs, and mindset so that all schools can give each student a gifted education? How can we recognize the genius, awaken the genius, and cultivate the genius in every child?" This presentation addresses concepts within my book titled, "Every Student Deserves a Gifted Education: 5 Shifts to Nurturing Each Student's Unique Strengths, Passions, and Talents".

This presentation challenges the conventional approach to gifted education, emphasizing the importance of 5 fundamental shifts. It seeks to transform our perception of gifted education, focusing on the unlimited potential within every student, regardless of their background. Additionally, the presentation will delve into well-supported inclusive practices capable of unlocking the untapped potential within every student.

This presentation has impacts for educators, professionals, policymakers, parents, and anyone interested in this subject. The goal of this presentation is to inspire participants to adopt these transformative shifts, fostering inclusive environments that nurture each student's unique strengths, passions, and talents.

Establishing High Quality Authentic Social Emotional Learning (SEL) within the Elementary Setting: Supporting the Needs of All Learners

Tracey Hulen, T.H. Educational Solutions
Ann Bailey Lipsett, Lipsett Learning Connection

ABSTRACT

We know that children develop at different rates, have unique sensory profiles and enter school with varied life experiences. Children are not born with social-emotional skills, but rather develop these skills over time and throughout their lives. McClelland, Tominey, Schmitt, and Duncan (2017) state that teachers report numerous students entering school without social-emotional skills ultimately having an impact on their learning. A meta-analysis published in 2011 (Durlak, Weissberg, Dymnicki, Taylor & Schellinger, 2011) and updated in 2017 (Taylor, Oberle, Durlak, & Weissberg, 2017) found that SEL programs showed a statically significant positive improvement on student behavior, attitudes, academic performance, and SEL skills in general. According to Maslow's hierarchy of needs children may not have access to academic learning until their basic physical and emotional needs are met (Huitt, 2007). Therefore, when we unite academics and social-emotional learning we bring more of a focus on the needs of the "whole child". To be successful, schools must prioritize relationships and create safe environments for learning (Aspen institutes, 2018). School's approaches and methods for establishing SEL vary widely, many with just a primary focus on aspects of the school environment, while others mainly direct their attention to social and emotional skills development. Regardless of a school's approach to SEL, high quality authentic social emotional learning should encompass aspects of relationship building, creating supportive and effective learning environments, as well as a focus on both academic and social-emotional skills development in order to best meet the needs of all learners in all learning domains throughout their academic careers.

Post Quantum Cryptography Readiness: A Framework and Review of Public Laws and Literature

Loreen Powell, Marywood University

ABSTRACT

The advent of post-quantum computers poses a potential threat to commonly used encryption algorithms. Quantum computers have the theoretical capability to break widely used encryption methods, such as RSA and ECC (Elliptic Curve Cryptography), by exploiting quantum algorithms like Shor's algorithm. To address this concern, governments and organizations are taking steps to prepare for the post-quantum era with federal laws like Public Law HR-7535 and NSM-10. These public laws aid in the mandate of various security measures, including the inventory of vulnerable cryptographic systems. As a result, there is a growing concern in the cybersecurity community about the need for post-quantum cryptography readiness. This presentation provides an overview of the theoretical overview of public laws, literature regarding post quantum cryptography readiness, and a multi-faceted framework for PQC readiness. This paper has practical implications for faculty, practitioners, and organizations.

Embracing Innovation in Marketing Education: Transforming Pedagogy in a Dynamic Landscape

Heather Morgan, Kennesaw State University

ABSTRACT

Marketing as we know it is forever changed. Major disruptions such as the Covid-19 pandemic, shifts in consumer behavior and technological advancements such as AI are rapidly changing the landscape. Educators are thus faced with the challenge of preparing students for success in a dynamic business environment. We simply must stay ahead of the game, and one way to do so is through implementing innovative pedagogy.

Innovative pedagogy requires that educators move from professor-directed to student-centered learning. While not a novel concept, its importance is arguably greater than ever. The integration of innovative pedagogy helps to address one major criticism of higher education- failure to properly equip students with marketable skills. Simulations, experiential learning assignments, student-AI collaboration assignments, and real-world case studies are instruments that educators can use to bridge the gap between theory and practice, while also fostering critical thinking and problem-solving skills, and inspiring creativity.

The purpose of this presentation is to facilitate a discussion around innovative pedagogy by emphasizing the immediate need for educators to adapt, highlighting benefits, showcasing best practices, demonstrating various assignments that can be utilized in Marketing education and encouraging adoption.

The contribution of the proposed presentation to marketing education is to encourage adoption of innovative pedagogy and offer suggestions to better equip students for a rapidly changing business landscape. The interdisciplinary nature of this topic makes it a good fit for NCCiT.

Using Generative Artificial Intelligence in Marketing Curriculum

Ronda Mariani, Commonwealth University – Bloomsburg Campus

ABSTRACT

This presentation explores integrating Generative Artificial Intelligence (GAI) technologies, namely HeyGen, Midjourney, ChatGPT, and Image Creator, within the context and application in college marketing classes. The aim is to share and assess these AI tools' effectiveness and pedagogical implications in enhancing digital marketing students' learning experiences and outcomes. This research contributes to the ongoing discourse on integrating GAI technologies in higher education. It provides insights into the potential benefits and challenges associated with incorporating HeyGen, Midjourney, ChatGPT, and Image Creator in digital marketing classes, shedding light on their role in shaping the future of marketing education. Additionally, the presentation offers practical recommendations for educators and institutions looking to harness the power of GAI to prepare students for the evolving demands of the marketing industry.

This presentation will be a participatory workshop. Individuals who want to participate should be prepared by having the following software access: ChatGPT, Canva, and Image Creator. An interactive project will be provided.

Innovative Techniques in Online Learning: A Deep Dive into Yellowdig's Gamified Community Platform

Melanie Wiscount, University of Illinois – Gies College of Business

ABSTRACT

In the ever-evolving landscape of higher education, the quest for effective, interesting, and collective online student engagement is paramount. Traditional online discussion boards, characterized by rigid requirements like posting once and replying twice weekly, that make it feel and look like an assignment, have long been the norm. However, this conventional model often lacks the dynamism and spontaneity that fosters genuine engagement between students.

Enter Yellowdig, a game-changing platform that has revolutionized the realm of online student discussions as well as resulting in student-created content. Unlike traditional platforms, Yellowdig promotes genuine student interactions, moving well beyond the "1 post, 2 replies" paradigm. By leveraging advanced gamification techniques, Yellowdig awards badges and points, instilling a sense of achievement and motivation among students. Also, when using Yellowdig in your course, there is no grading required! The platform's data-centric approach provides insights into user engagement, with compelling metrics to cultivate the type of community and instructor presence the fuels the best kind of learning by sharing.

Furthermore, Yellowdig emphasizes both qualitative and quantitative measures of engagement, from student-to-student interactions to positive end-of-course survey results. This presentation aims to unpack the innovative strategies employed by Yellowdig to boost online student engagement, which becomes an additional student-created course resource, highlighting its transformative potential in reshaping the future of digital learning and community in higher education.

Join me to explore the cutting-edge methods that are setting Yellowdig apart in the crowded field of online education technology. Bring your curiosity and your passion for innovation; let's reimagine the future of online learning together.

Zero-Knowledge Proofs: Foundations, Real-World Applications, and Use Cases

Andrew Mangle, Bowie State University

ABSTRACT

Zero-knowledge proofs (ZKPs) offer a cryptographic approach to increase data privacy, security, and trustworthiness. ZKPs have emerged as a transformative solution to address the pressing challenges of trust and data privacy. ZKPs are explored via foundational concepts, historical evolution, alternative approaches such as homographic and lattice-based encryption, real-world applications in domains such as blockchain and secure authentication, and potential use cases. By bridging the gap between foundational knowledge and tangible use cases, consumers will gain a robust understanding of ZKPs' potential and their pivotal role in crafting a more secure digital future.

Digital Accessibility in the Workplace

Kyle Fromert, Accenture Federal Services

ABSTRACT

The outbreak of COVID-19 forced many businesses and educators to rely on a paperless approach, using websites, applications, and other digital media to engage and assist clients or students. While the utilization and creation of websites, applications, and digital media prove highly beneficial, they pose several challenges that hinder individuals with disabilities from obtaining equal access to these resources (Powell et al., 2022). This presentation aims to explain the significance of digital accessibility within the workplace and provide valuable insights and resources to assist organizations in achieving digital accessibility for all individuals. This presentation has practical impacts for businesses, managers, institutions, and faculty.

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Virtual Community Citizenship Behavior: A Social Relational Perspective

Tung (Francis) Cu, Northeastern Illinois University

ABSTRACT

The rapid digitalization of society has given rise to virtual communities that transcend geographical boundaries and connect people based on shared interests, goals, or experiences. Among various themes emerging in academic research regarding virtual communities, one area that has attracted considerable attention is citizenship behavior.

The aim of this study was to dive into both relational and collective facets to comprehend community citizenship behaviors within online community settings. It sought insights into how community interactions inspire users to freely contribute and maintain their memberships. To this end, the study introduced a social relational model, merging existing social and managerial theories related to social communities. Given the nature of the research, the model was centered on the dynamic relationships between collective constructs such as sense of community and citizenship behavior, and relational constructs such as trust and loyalty. To test the proposed model, the study conducted a survey on 247 users in different online communities.

The results robustly supported the hypothesized relationships. They distinctly revealed that sense of community, trust among community members and community loyalty can enhance citizenship behaviors. Importantly, a sense of community emerged as the most significant predictor of such behaviors, with trust and loyalty serving as mediating factors. This suggests that, in an online setting, users who feel a deeper emotional bond, a stronger sense of belonging, and possess greater influence within the community are more likely to engage in voluntary activities, collaborate more closely with different community parties, and actively participate in community programs.

Exploratory Analysis of Correlation between Personality Traits and the Success of Computing Major Transfer Students

Sherrene Bogle, California State Polytechnic University
Shebuti Rayana, The State University of New York (SUNY) at Old Westbury
Palvi Aggarwal, University of Texas El Paso
Claire MacDonald, University of Texas El Paso
Xiwei Wang, Northeastern Illinois University
Yun Wan, University of Houston
Kay Vargas, California State Polytechnic University
Victor Diaz, California State Polytechnic University

ABSTRACT

Underrepresented minority (URM) students are disproportionately enrolled in community colleges (CC) yet have lower retention rates than their peers. Of the students enrolled in community colleges, 29% are first-generation along with 42% and 52% of all Black and Hispanic students beginning their academic journey at CC. While the literature addresses some personal and academic factors that impact a student’s likelihood to continue and complete their degree, a large degree achievement gap still persists.

Hence, this study was conducted to explore the specific roles that personal characteristics and social factors play in URM transfer student success in Computer Science. Specifically, factors within the context of Bandura’s social cognitive theory (SCT) were explored. This study utilized one-on-one interviews with 15 students. The interviewees were selected from a larger pilot group that previously completed a questionnaire on demographics and academic factors impacting their transfer decisions. The interviewees self-assessed their abilities in the following three categories of the SCT: self-efficacy (SE), outcome expectation (OE), and goal setting (GS). This data was then analyzed to understand if transfer students had the expected self-concept under the SCT relative to general transfer student success. Results revealed that the group of post-transfer students’ average rating was slightly higher than the pre-transfer group in both measurements of SE and GS. This research will help stakeholders provide appropriate resources that can boost the SCT factors of transfer students and their overall success.

Understanding Human-Machine Teaming for Autonomous Technology

Jiyoon An, Fayetteville State University

ABSTRACT

Autonomous technology is pervasive in everyday life. Advanced Driver Assistance Systems (ADAS) have brought comfort in lane keeping and parking assistance to drivers (Li & Huang, 2022). Chatbot systems have become a companion for work and home to answer your questions backed by the Large Language Model (LLM) (Ding & Goldfarb, 2023).

Scholars examining Human-Machine Teaming (HMT) argue that when autonomous technology is seen as a teammate rather than a tool, teaming between technology and humans thrives through the mechanisms of coordination, mutual learning, and collective goal pursuit (Walliser et al., 2019). This paper explores the under examined area of Human-Machine Teaming to provide insights into autonomous technology as a teammate.

A bibliometric analysis (Donthu et al., 2022) has been conducted to understand the intellectual foundations of HMT. 181 papers were collected by the Web of Science database with the keyword Human-Machine Teaming. The research overview was presented by publication trend analysis by year, outlets, citations, and co-occurrence keyword analysis to identify five clusters (automation and trust, communication and transparency, cybersecurity, ethics, and collaboration). Co-citation and bibliographic coupling analyses were used to identify the retrospective and prospective summary of research findings. Based on the bibliometric analysis, the Antecedents-Decisions-Outcomes (ADO) framework (Paul & Benito, 2018) was applied to draw insights for academics, managers, and policymakers to utilize autonomous technology.

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How will Generative AI Policies Intersect with Academic Freedom and What are the Implications for Higher Education Stakeholders?

Christopher "Allan" Hubbard, Lindsey Wilson College
Dr. Steve Hallman, Lindsey Wilson College

ABSTRACT

The rise of generative AI has ignited significant discourse in higher education, garnering attention and scrutiny from scholars and practitioners. Central to this discourse is a question about policy creation: how will generative AI policies intersect with the fundamental concept of academic freedom, which has long been regarded as the bedrock upon which education is built, and given those policies what are the implications for higher education stakeholders? No one knows what the future of AI will mean for higher education, but most indications point to generative AI becoming an accepted and widely used technology in all areas of higher education. However, there is a dearth of quality discussions on how higher education stakeholders can make sense of the uncertain and ever-evolving intricacies of AI policy creation in academia.

Drawing on compiled data about generative artificial intelligence (AI) policies from public websites, open access documents, webinars, articles, and eight high-ranking U.S. academic institutions, this descriptive analysis frames its findings along a seminal sensemaking schema (Weick, 2003) that is designed for social dialog that allows people to understand ambiguous or confusing issues or events (Brown, Colville, Pye, 2015).

This presentation proposal uses a seminal sensemaking model (Figure 1, Weick, 1993) to develop an AI education policy sensemaking schema (Coeckelbergh, 2021, Malmborg, 2022) to help higher education stakeholders better understand how to move forward in the face of the unexpected or unanticipated (Dougherty, 2020) rise of generative AI while preserving the integrity of academic freedom. Based on the findings, this work proposes a generative AI sense-making scale to address the multifaceted implications of AI integration in university teaching and learning and its subsequent impact on its stakeholders.

The purpose of this proposed presentation is to explore the impact of generative AI on higher education, particularly its interaction with academic freedom. We address the question of how AI policies will affect the foundation of education, given the likely widespread adoption of generative AI. Despite this impending shift, there is a lack of substantive discussions on navigating AI policy creation in academia. By utilizing a sensemaking model, we develop an AI education policy schema to assist higher education stakeholders in understanding and adapting to this evolving landscape while preserving academic freedom. Our presentation introduces a generative AI sense-making scale, offering insights into the complex implications of AI integration in education.

This research proposal is grounded in its contributions to the field of education and NCCiT's mission by addressing the important intersection of generative AI and higher education. It recognizes the importance of academic freedom in the face of AI adoption, which fills a crucial knowledge gap in AI policy discussions within academia.

By offering a sensemaking model and AI education policy schema, the proposal will equip higher education stakeholders with the means to navigate the evolving AI landscape while safeguarding academic freedom. Moreover, this proposed presentation introduces a novel generative AI sense-making scale that will provide nuanced insights into the multifaceted implications of AI integration in higher education policy creation.

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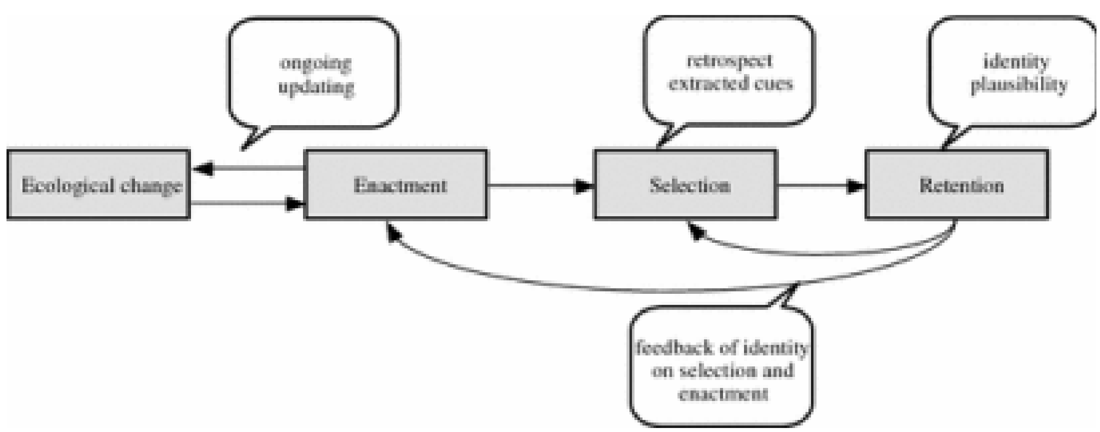
Figure 1 - Sequence of Sensemaking (Weick, 2003)



The Dynamic Transformations of the K-12 Education

Daniel Powell, North Pocono School District

ABSTRACT

The K-12 education landscape is dynamic, constantly evolving as educators, policymakers, and communities adapt to the evolving needs of students and the ever-changing demands of the world. These trends underscore the significance of flexibility, innovation, and a steadfast commitment to delivering quality education to all students. This paper explores literature and provides real-world examples of each of the 15 dynamic changes. The real-world examples presented will aid in participant discussions. This paper has practical impacts for any educational setting, administrator, and faculty member.

Positive Use of Smartphones in the Secondary Classroom

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ABSTRACT

Smartphone use in modern society is not only commonplace, but also part of most cultures. The way humans communicate, interact, and perform various functions has changed significantly over time and the evolution of cellular technology has enabled this to happen. Cellular devices are highly accepted by younger members of society, which are commonly referred to as digital natives, meaning they were born into the technology. However, the use of such devices by teenagers in a secondary educational environment can have both positive and negative impacts. When use of such devices is not monitored or kept in check, social-emotional and behavioral problems may arise in adolescents (Choliz, 2010, 2012). A strong relationship exists between demographic variables such as age and gender and mental health variables including behaviors such as aggressiveness, depressed mood, and anxiety (Ha, Chin, Park, Ryu, & Yu, 2008; Kim et al., 2015). Shyness was also a variable linked to cell phone addiction (Casy, 2012; Park, 2005) as well as loneliness (Hjenaabadi, 2016; Naderi & Haghshenas, 2009). Warzecha and Pawlak (2017) found that approximately 35% of secondary students were at risk of becoming addicted to Smartphone use and 4% were addicted. The authors also found that females were more likely to become addicted than males. Most students in the study were said to receive their first smartphone by age 10 and more males than females had a smartphone in the findings (65% and 60% respectively). Smartphone use to access social media sites by teenagers may have a significant effect on self-esteem (Ha et al., 2008; Niemz, Griffths, & Banyard, 2005). Studies have found that self-esteem in teenagers increases as the addition level of smartphones decreases, showing a correlative, inverse relationship (Ha et al., 2008; Leung, 2008; Niemz, Griffths & Banyard, 2005; Wang et al., 2017). Smartphones can be an effective learning tool that fosters engagement and positive interactions in a secondary classroom (Sabron, Hashim, Abdullah, & Shamsudin, 2020). The use of smartphones has shown to be considered a fun way of learning that reduces students' anxieties at the secondary level (Redmond, Heffernan, Brown, & Henderson 2018). Students who use their smartphones in a positive way find it to be both a learning and social engagement tool (Cha & Seo, 2018). A major finding is that the use of a smartphone clicker app can be used by students in the classroom, which increases a teacher's willingness to use these devices in the classroom (Aljaloud, Billingsley, & Kwan, 2019). Inferences from former research can lead educators in a secondary classroom to believe two things: Smartphone use by teenagers can lead to various social-emotional problems and behaviors. Two, if used properly within a secondary school, can be an invaluable resource for learning and student engagement. Since the technology is not likely to go away, tapping into it may be highly beneficial. This paper explores literature and provides real-world examples of why and how educators can possibly tap into using cell phones within the classroom. The real-world examples presented will aid in participant discussions. This paper has practical impacts for any educational organization and faculty member.

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What to Expect in The Day to Day Role of a Rural K-12 Superintendent in 2023: Potential Challenges and Responsibilities

Daniel Powell, North Pocono School District

ABSTRACT

The day-to-day role of a superintendent in K-12 education has expanded to encompass a broader range of responsibilities related to safety and crisis management, professional development in areas like mental health and gender crisis, and budget management. Superintendents are now seen as educational leaders who must adapt to changing circumstances and prioritize the well-being of students and staff while managing the financial health of their districts. This paper explores the literature and provides scenarios of what rural K-12 Superintendents might face in their day-to-day role as Superintendent of Schools. This paper has practical impacts for any educational setting, administrator, and faculty member.

Investigation of Interpersonal Competencies in Early-career Mutual Insurance Professionals

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Nicholas King, Alvernia University
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ABSTRACT

A problem exists between employers and individuals as employers seek to hire individuals with non-technical skills who can add value and leadership to their companies. These non-technical skills are hard to recognize and identify when interviewing candidates. The researcher further defined, clarified, and investigated interpersonal competencies among early-career insurance professionals. The research was conducted through semi-structured interviews with 16 mutual insurance executives and two focus groups each consisting of five mutual insurance executives. These executives were selected and volunteered from five Pennsylvania mutual insurance companies. Interviews were transcribed and coded to find recurring themes pertaining to the competencies needed in early career insurance professionals. Controlling emotions was the most desired competency from insurance professionals. As these professionals converse with customers and coworkers on a daily basis, controlling emotions and de-escalating potentially confrontational conversations is essential. Verbal and written communication and collaborative teamwork were the next, most recurring competencies necessary for early career insurance professionals to possess. This research benefits employers in their hiring practices and in identifying insurance professionals for leadership and promotion opportunities.

The National Conference on Creativity, Innovation, and Technology (NCCiT)

2023 Conference Proceedings

At the first NCCiT Conference, there were over 100 attendees, approximately 55 presenters, and 33 presentations. Of the 33 presentations presented at the NCCiT, those papers/abstracts that were completed by the authors and submitted to the Proceedings are listed here. The NCCiT Conference Proceedings have undergone a double-blind peer reviewed process.

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