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PROCEEDINGS OF THE 2020 UNDERGRADUATE RESEARCH CONFERENCE

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PAPERS AND EXTENDED ABSTRACTS PRESENTED AT
THE UNIVERSITY OF LOUISIANA AT LAFAYETTE

Data Preprocessing of Big Geological and Hydrological Data Sets

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ABSTRACT

In this study, the implementation of the image processing and optical character recognition techniques are investigated to convert a large number of handwritten geotechnical information into the spreadsheets to be further analyzed for groundwater modeling and study for the Southeastern US region. The automated procedure was successfully tested to convert the scanned data into images, crop the images to grab the desired pieces of information, and convert the data from the image format to ASCII files. The proposed method was proved to be highly promising for efficient management of the unused scientific data in the form of scanned handwritten documents. The approach presented in this paper significantly reduces data manipulation time and accelerates the big data preparation to train an accurate and comprehensive machine learning model.
Key words: Machine learning, OCR, Vision API, python.

1. INTRODUCTION

Water has always been an indispensable substance for plants and animals, without which life is unimaginable on earth. Various interconnected sources such as oceans, seas, rivers as well as groundwater provide water. One of the vital water resources is groundwater, which is responsible for recharging for lakes and rivers. The aquifer is essential for both industrial usage and irrigation purposes as well. It supplies 51 percent of the entire drinking water and 99 percent of the rural US population (Groundwater Foundation, 2020)**.** Twenty-five percent of the freshwater in the United States, including 43 percent of the freshwater for irrigation purposes, is supplied by groundwater. Only in the United States, there are more than 15.9 million active wells (American Geosciences Institute, 2020). In the southeastern US, Alabama, Mississippi, and Louisiana, groundwater provides about 40 percent of the required water for all public supply, agriculture, industry, mining, etc. Some states like Mississippi are more dependent on the groundwater with 68 percent of freshwater withdrawals coming from this source (American Geosciences Institute, 2020). Excessive extraction of the groundwater in the Southeastern US has culminated in depletion of the groundwater by an average rate of 13.6 km^2/year. However, an accurate estimation of the available groundwater reservoir is hard to obtain due to complex hydraulics making the prediction difficult for the numerical models that rely mostly on parametrized formulae (Galloway, 1977). Therefore, the observational data from boring samples are valued sources for data assimilation, calibration, and verification for the numerical models (Schlumberger, 1972; Bassiouni, 2008). Figure 1 presents the location of sample well logs in the Baton Rouge area, LA ((Pham & Tsai, 2017).

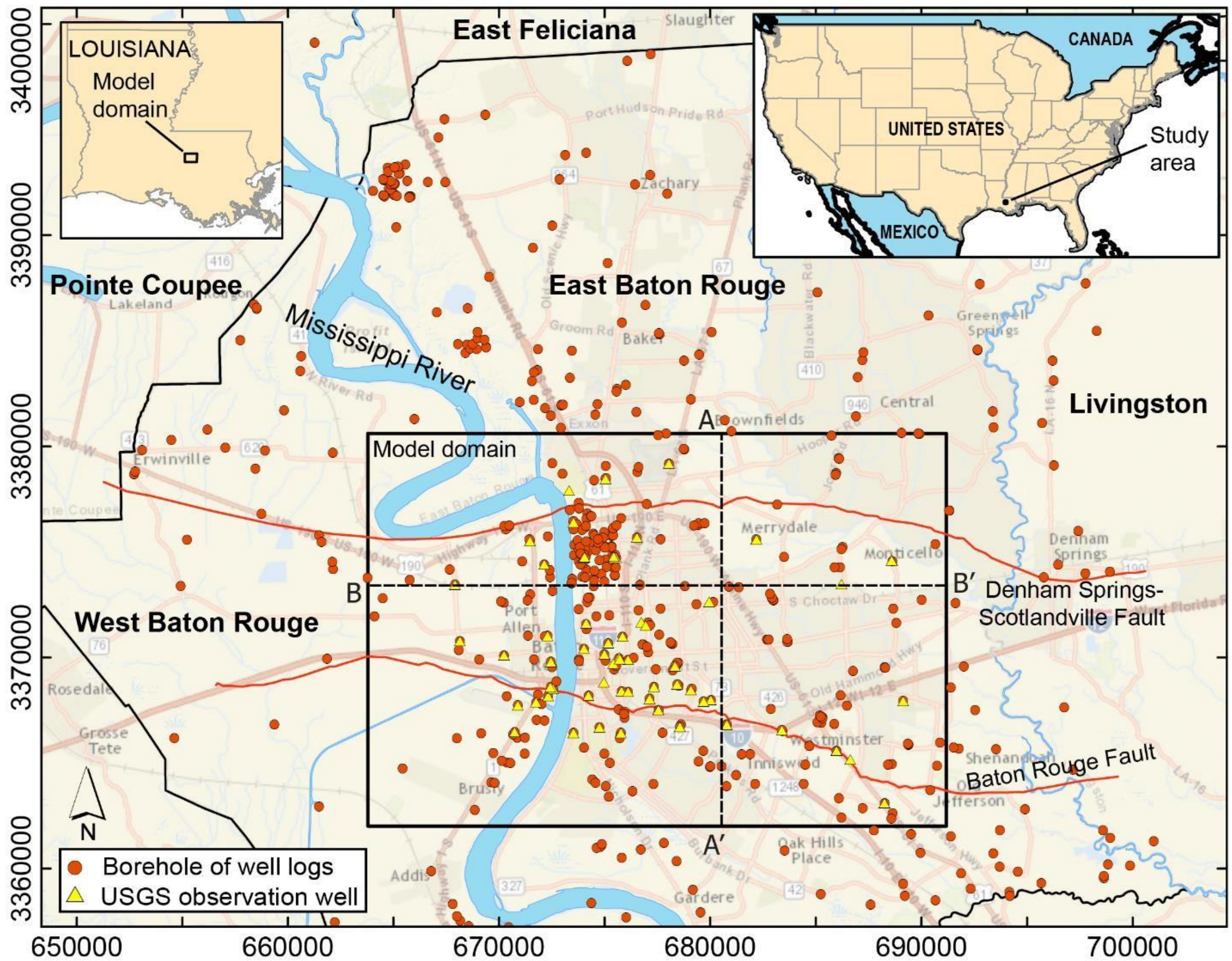


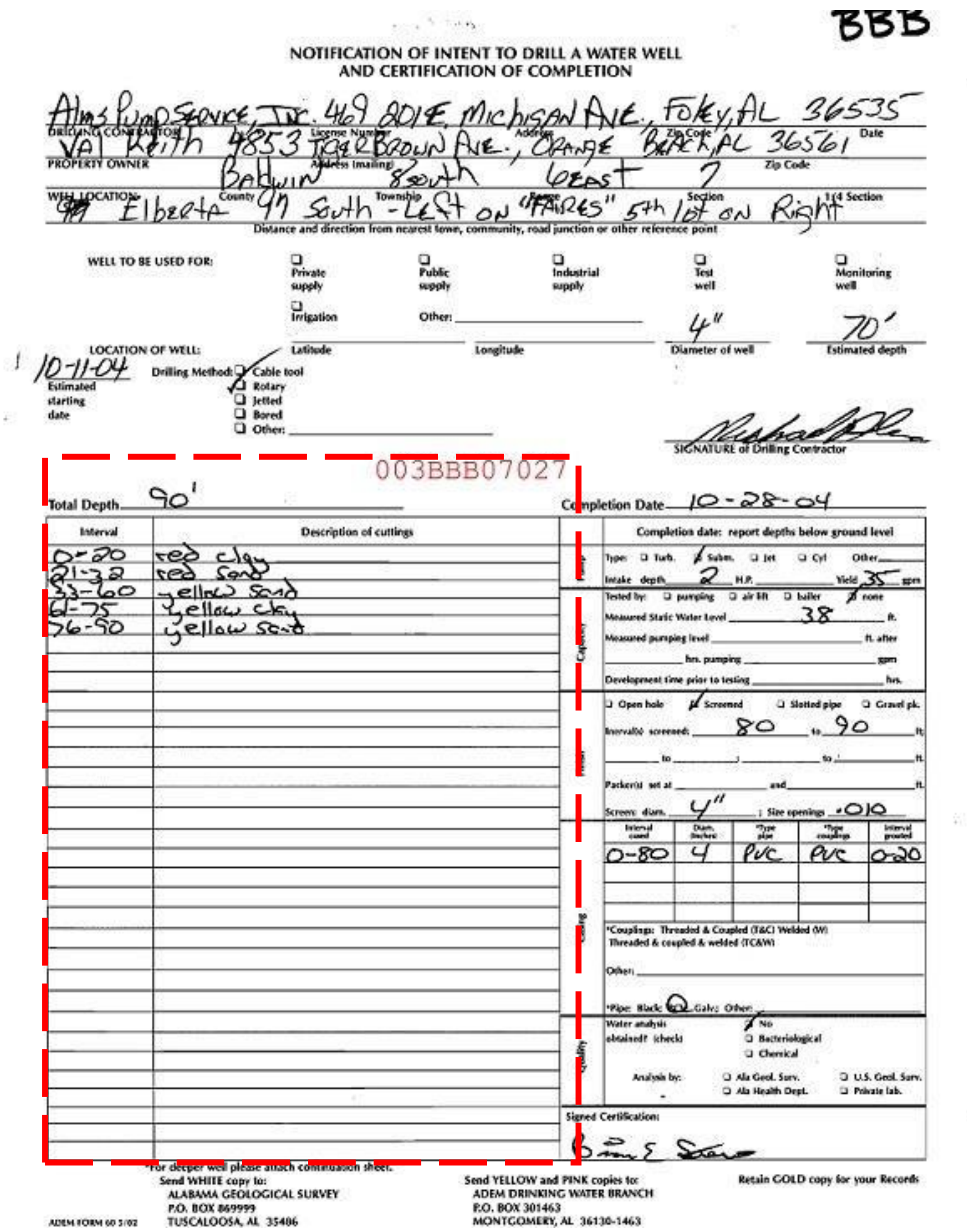
Figure 1. Distribution of boreholes of well logs (circles) in the Baton Rouge area (taken from Pham & Tsai, 2017).

Despite the abundance of observation during the past decades, the geotechnical information obtained from the bores has been recorded in paper format and filed in the storages. The effective and pervasive usage of such a bulky data resource has always been a challenge. Converting this huge unstructured amount of data to the structured and readable dataset for further analysis and calculation with the help of manpower took more than 10 years only for the state of Louisiana. With a boost in technology and the widespread use of machine learning techniques, new opportunities are emerged to utilize this handwritten data for the purpose of groundwater estimation and analysis. Google API (Google Vision API, 2020) and Microsoft Cognitive Services (Microsoft Cognitive Services, 2020) are two examples of the tools that can introduce object recognition to mitigate this problem. Selective search or Convolutional Networks are the main methods to apply object recognition technique (van de Sande, Uijlings, Gevers, & Smeulders, 2011; Sermanet, et al., 2014; Neves & Lopes, 2016) .The goal of this work is to develop an automated method to convert all scanned information obtained from the bores to the structured file format that is easily readable for further modeling and engineering analysis.

Considering that construction of each well costs about 200,000 USD, accurate extraction of data from each handwritten page is of paramont importance.

2. METHODOLOGY

The bulky geotechnical data from the bores are scanned and saved in .pdf files. All of the files follow the same predefined template. Some forms are filled by hand, and some are filled by typing machine. A sample of the handwritten scanned file containing the geotechnical data, recorded on October 2004, is depicted in Figure 2.


BBB

NOTIFICATION OF INTENT TO DRILL A WATER WELL
AND CERTIFICATION OF COMPLETION

Alma Pump Service, Inc. 469 8014 E. Michigan Ave., Foley, AL 36535
DRILLING CONTRACTOR License Number Address Zip Code Date

Val Keith 4853 Tiger Brown Ave., Orange Beach, AL 36561
PROPERTY OWNER Address (mailing) Zip Code

Baldwin 8 South 6 East 7
WELL LOCATION County Township Range Section 1/4 Section

Elberta 97 South - Left on "Faires" 5th lot on Right
Distance and direction from nearest town, community, road junction or other reference point

WELL TO BE USED FOR: ☐ Private supply ☐ Public supply ☐ Industrial supply ☐ Test well ☐ Monitoring well ☐ Irrigation Other:

LOCATION OF WELL: Latitude Longitude 4" Diameter of well 70' Estimated depth

10-11-04 Estimated starting date

Drilling Method: ☐ Cable tool ☑ Rotary ☐ Jetted ☐ Bored ☐ Other:

SIGNATURE of Drilling Contractor

003BBB07027

Total Depth 90'

Completion Date 10-28-04

Interval	Description of cuttings
0-20	red clay
21-32	red sand
33-60	yellow sand
61-75	yellow clay
76-90	yellow sand

Completion date: report depths below ground level

Type: ☐ Turb. ☑ Subm. ☐ Jet ☐ Cyl Other
Intake depth 2 H.P. Yield 35 gpm
Tested by: ☐ pumping ☐ air lift ☐ bailer ☑ none
Measured Static Water Level 38 ft.
Measured pumping level ft. after hrs. pumping gpm
Development time prior to testing hrs.

☐ Open hole ☑ Screened ☐ Slotted pipe ☐ Gravel pk.
Interval(s) screened: 80 to 90 ft.
Packer(s) set at and ft.
Screen diam. 4" ; Size openings .010

Interval cased	Diam. (inches)	*Type pipe	*Type couplings	Interval grouted
0-80	4	PVC	PVC	0-20

*Couplings: Threaded & Coupled (T&C) Welded (W) Threaded & coupled & welded (TC&W)
Other:
*Pipe: Black Galv. Other
Water analysis obtained? (check) ☑ No ☐ Bacteriological ☐ Chemical
Analysis by: ☐ Ala Geol. Surv. ☐ Ala Health Dept. ☐ U.S. Geol. Surv. ☐ Private lab.

Signed Certification:

*For deeper well please attach continuation sheet.

Send WHITE copy to: ALABAMA GEOLOGICAL SURVEY P.O. BOX 869999 TUSCALOOSA, AL 35486

Send YELLOW and PINK copies to: ADEM DRINKING WATER BRANCH P.O. BOX 301463 MONTGOMERY, AL 36130-1463

Retain GOLD copy for your Records

ADEM FORM 60 5/02

Figure 2. Scanned file of an observational record of geotechnical data for a sample bore. The cropped area of interest is shown as a red dashed line.

The first task is to convert the scanned forms to the desired format we need. As such, we have developed three codes: The first step pertains to converting the .pdf file to an image one. In the second step, the essential parts of each image file are automatically cropped. Finally, the cropped handwritten text is converted to machine-encoded text. All the coding is done in the python environment for which a python 3.7 version is incorporated. The details of each of the aforementioned steps are as follows:

1.1 Converting from .pdf to an image file

The .pdf files in the first step are converted to .jpg file format. In this process, the following three libraries are employed: Poppler, pdf2image, and Pillow. The Poppler library is used for pdf rendering based on xpdf-3.0 codebase, which is the core for pdf2image library. The pdf2image library is used for converting .pdf file format to .jpg or .png file format. It converts .pdf to a sequence of PIL image objects. The Poppler is utilized by pdf2image library to execute the conversion. Then, the resulting image of pdf2image library is returned as a PIL image object (OpenGenus IQ, 2020).

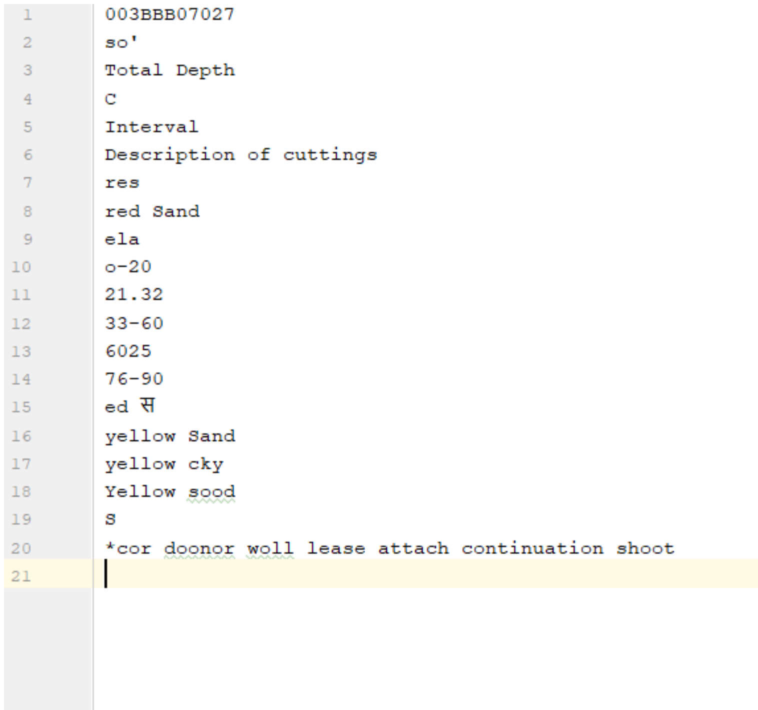
1.2 Cropping of the image file

After converting the .pdf to an image, the next task is to grab the essential parts of the image that include the important geotechnical information related to depth and sediment type for each of the soil layers. To automize this process, the image processing capability of the python is incorporated. To do so, the newest version of PIL, i.e., Python Image Library, also known as Pillow, is selected as the best choice (Pillow, 2020). The cropped product image is generated by introducing the pixel information at four corners of the desired part of the image into the crop method of the Pillow library. The cropped area of the image for Figure 2 is depicted as a dashed line.

1.3 Converting the image into ASCII file

Upon generating the cropped image, the subsequent step and the most important one would be to develop a method for the code to automatically identify the essential information from the handwritten image file and write them into an encoded machine text. This process is accomplished using Optical Character Recognition (OCR) tools. OCR technology converts the scanned paper documents or pdf files, or images into data that can be edited and/or searched (ABBYY, 2020). Google cloud provides one of the most powerful OCR tools, called Vision API. Google clouds Vision API provides pre-trained machine learning models to analyze and classify the image into predefined categories (Google Vision API, 2020). This tool provides capabilities to detect objects and faces, identify popular places and product logos, and discover printed and handwritten texts (Google Vision API, 2020). Google Cloud Vision API was imported as a package into python code and employed to convert the handwritten into editable text and to save it to an ASCII file. In order to run the program, the Vision API code needs to communicate with the google cloud platform through an internet connection. A snapshot of the result of the conversion using Vision API is shown in Fig. 3.

Despite sporadic mis-conversion issues, the newly developed method incorporated in this study provides a useful tool saving substantial time and manpower for data interring and manipulation. The flowchart of the proposed procedure to convert the handwritten geological data to .csv files is shown in Fig. 4.



```
003BBB07027
so'
Total Depth
C
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Description of cuttings
res
red Sand
ela
o-20
21.32
33-60
6025
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ed स
yellow Sand
yellow cky
Yellow sood
S
*cor doonor woll lease attach continuation shoot
```

Figure 3. Converted text file from the cropped region of the scanned handwritten document in Fig. 2 using the Vision API platform.

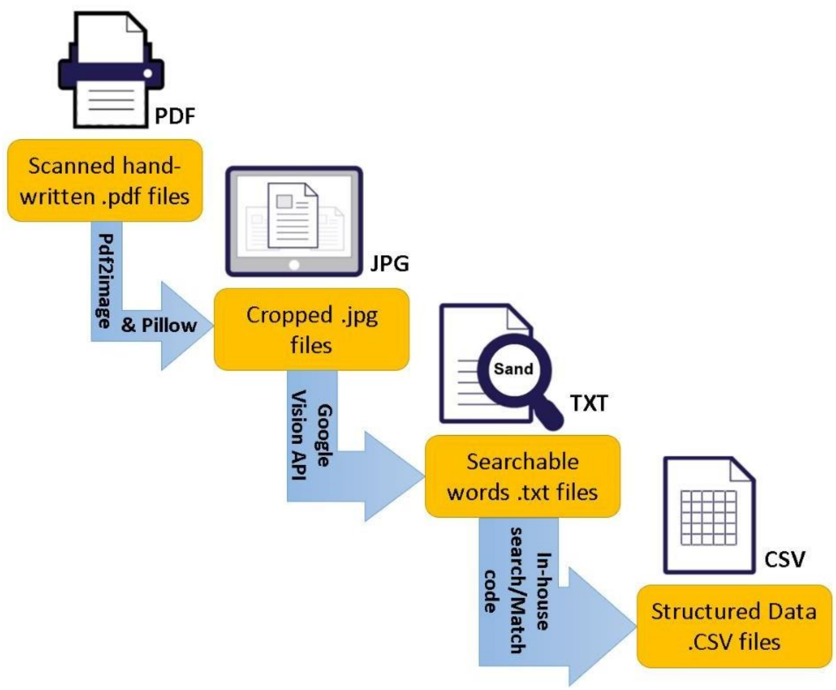

Figure 4. Flowchart of the proposed procedure to convert the handwritten data to .csv files.

3. DISCUSSION AND FUTURE WORKS

After accomplishing the conversion process, the text files are scanned by another code to correct miss-converted words. Since only limited technical terms are used in the geological datasheets, automatic search and replacement of the miss-converted words would become accessible. For instance, any first-hand labels digitized from machines, containing "Gravel", "gravel", "ravel", "rave", "avel", etc, would corrected as "gravel" in the final text file. Then, based on the order and patterns of numbers and keywords in Fig. 3, the text files will be interpreted to generate the corresponding desired .csv file format. In this step, the important consideration is to locate the numbers and texts in the .txt file and transfer them to the correct location in the .csv file, as shown in Fig. 5. Thereupon, the .csv files are quality checked to ensure not having wrong or missing data, followed by saving as .csv files as the final product to be used by machine learning algorithms.

	A	B	C	D	E	F	G	H
1	Name	Datum	red clay	red sand	yellow sand	yellow clay	yellow sand	
2	003BBB07027	0	20	32	60	75	90	
3								
4								
5								
6								
7								

Figure 5. The .csv file as a final product to b used by machine learning analysis.

The .csv files obtained from each well log will serve to create a large spatiotemporal database that will be employed to address groundwater shortage, aquifer recharge, subsurface properties, and surface-subsurface interactions at multiple spatial and temporal timescales using python-based machine learning algorithms. The couples modeling and data fusion experiments will mitigate uncertainty in groundwater simulations and bridge between groundwater/surface water interactions, currently missing in hydrologic models (Clark , et al., 2015).

During this process, some problems need to be considered as critical steps for improvement of the data conversion and preparation. For instance, misspelled or inaccurately detected words from the handwritten image is very important to effectively coded. In some cases, the code could not extract the data due to bad or complicated handwriting. Another issue is that Google Vision API does not convert in the exact order that exists in the image. Therefore, the correct reordering of the data is a critical step after the conversion process.

This paper addresses the application of the image processing and OCR techniques to extract soil data from the bulky handwritten geotechnical data gathered over the decades for the wells in the Southeastern US. A large number of these data and high manpower demand impedes the manual extraction and interring of the data, vitalizing the automated computer-based alternative methods. Using OCR technology, the scanned handwritten data was successfully converted into an image and then into the text files that could be further read as spreadsheets. The proposed method was found to be capable of saving substantial time and serving towards more efficient use of manpower resources. The final products would further be used for validation of the calibration of the multi-state-wide groundwater management models.

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Simulation of Quantum Cheques Circuits in Five-qubit IBM Quantum Computer

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ABSTRACT

Quantum computers could spur breakthroughs in computer science, computational modeling, artificial intelligence, commerce, materials science, chemistry, and physics. A cheque is a printed document issued by an account holder to order the bank to pay a specified amount of money to the party carrying the cheque. It is much essential as taking a huge amount of money physically is not safe. However, this physical form of cheque still faces the problem of forgery and misuse. In order to avoid physical handling as well as the delays associated with manual processing of cheques and, most importantly, to improve the security of the transaction, a concept of quantum cheques is proposed. By using a quantum cheque, it is estimated that any sort of forgery is almost impossible. In the current work, the quantum cheque transaction is simulated and run experimentally by the IBM quantum experience platform using 5-qubit quantum computers. For this, quantum circuits for quantum cheque generation and quantum cheque verification are designed and tested. Our results are verified by theoretical results achieved by simulation.

1. INTRODUCTION

Quantum computing is a revolutionary technology where computation is relied on qubits by using quantum-mechanical phenomena, namely superposition (Procopio,2015),entanglement (Satyajit, 2018), and interference (Shiekh, 2006). Qubit is the fundamental entity required for the processing of quantum information. A qubit is an analogy of a classical bit (De Lima, 2019). However, there exist more than two states of information storage. Hence, quantum computers are more advanced, fast, efficient, and highly sophisticated than today's supercomputers. The development of quantum computers is at the early stages. IBM quantum is one such initiative that provides the platform for solving complex problems (Khetawat, 2019, Dash, 2020, Mahanti, 2019 and Bochkin, 2020). A free web-based interface, IBM Quantum Experience (IBM QE), is a versatile experimentation platform used extensively for solving various computational problems and testing new quantum applications. It provides users a facile process to connect with the IBM cloud-based 5 – qubit quantum computer (Wei, 2018). Numerous quantum computational studies and algorithms for visualizing various key phenomena in a wide range of fields, including physics (Melko, 2019 and Anupam, 2013), chemistry (Jarrod, 2014), artificial intelligence (Dunjko, 2018), have been performed and tested successfully. Quantum tunneling (Pandey, 2019), the realization of quantum lockers, simulation of Klein Gordon equation, Bell states (Sisoda, 2020), entropic inequalities are a few of the illustrated applications.

Herein, by utilizing IBM QE, we demonstrate the quantum cheque (Behera, 2017 and Moulick, 2016) transaction process experimentally as described by Moulick et al. and Behra et al. With the advancement of e-commerce, efficient payment methodologies, and improvement in the security of money transactions have become the urgent requirement. The Quantum cheque scheme is revolutionary to the current e-payment gateways, offering a more efficient e-payment experience. This scheme works effectively both for offline and online transactions. In online mode, the smart cards facilitated with quantum memories are used to realize transactions. In contrast, in offline mode, the account holder needs to collect a quantum checkbook from the bank and then generate the cheque, which is termed as quantum cheque generation. The generated cheque is issued to the vendor, and the vendor will present the cheque in the bank where it is verified, which is termed as 'quantum cheque verification,' and then the relevant transaction is released. In the current work, we design quantum circuits for quantum cheque generation and verification processes. We demonstrate that the theoretical results are in correlation with the experimental results.

2. QUANTUM CHEQUE EXPERIMENTS SIMULATED USING IMB QE

Quantum circuits for cheque generation and verification are designed using the four quantum gates: (1) Hadamard (H) gate that rotates the states $|0\rangle$ and $|1\rangle$ to $|+\rangle$ and $|-\rangle$ respectively, and is used for the superposition of gates. (2) T gate that is equivalent to RZ for the angle $\pi/4$. Fault-tolerant quantum computers will compile all quantum programs down to just the T gate and its inverse, as well as the Clifford gates. (3) Tdg gate that is an inverse of the T gate. (4) CX gate that is a controlled X gate, also known as a controlled-NOT gate. CX gate works on two qubits; one is a control, and the other is a target. CX gate performs an X function whenever the target is in $|0\rangle$ state. Finally, measurement is an irreversible operation, also known as the z basis or standard computational basis. The operation can be used to implement any measurement when combined with gates.

The quantum circuit designed for quantum cheque generation using the IBM QE interface is shown in Fig. 1. In the typical 5-qubit quantum circuit, the first three qubits are related to the processes that occur under the control of the account holder, i.e., generation and signing of the cheque. In contrast, the fifth one is with the bank for processing the transaction. The fourth qubit is unused. The quantum cheque generation process mainly relies on the 3rd qubit of the account holder and the 5th qubit called a bank. On computing the H, T, Tdg, and CX gates sequentially on $|0\rangle$ with a phase angle of $\pi/8$, it is expected from simulation results that $|0\rangle$ has the probability of 85% while $|1\rangle$ has the probability of 15%. The results obtained on running experiments with 1024, 4096, and 8192 shots are shown in Table 1.

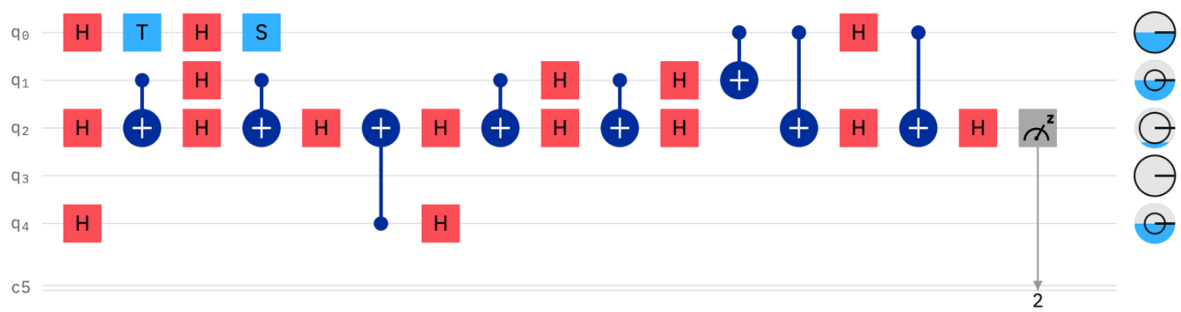

Figure1. Schematic of the quantum circuit implemented for quantum cheque generation on the IBM Quantum Experience platform.

***Table 1**. Experimental results on running the quantum verification circuit displayed in figure 1 for 1024, 4096, and 8192 number of shots.*

Number of shots employed	Measurement probability of $|0\rangle$ state (%)	Measurement probability of $|1\rangle$ state (%)

Experimental		
1024	76.27	23.73
4096	71.44	28.56
8192	80.85	19.15
Simulation	85.35	14.64

Figure 2 shows the quantum circuit used for the quantum cheque verification on IBM QE. Here, both the 2nd qubit and 3rd qubit are considered as |0⟩. From computational results, the probability of 1 is estimated for state |0⟩. The results obtained on running the quantum circuit are shown in Table 2. The values in Tables 1 and 2 indicate that the experimental results are closer to simulated results by running experiments with a different number of shots. The obtained noise can be low even with a large number of gates demonstrating that the quantum cheque transactions can be realized with better accuracy.

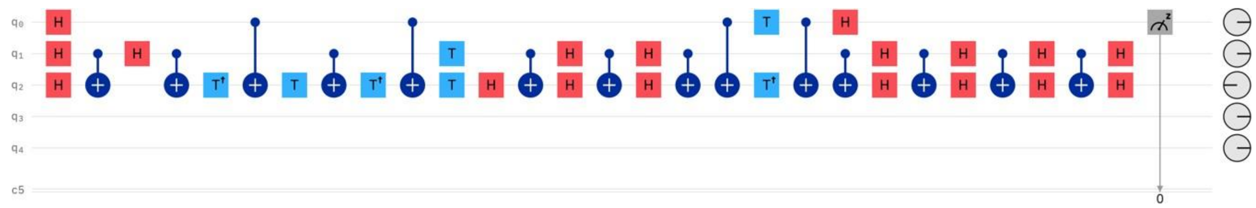

Figure 2. Schematic of the quantum circuit used for quantum cheque verification on the IBM quantum experience platform.

Table 2. *Experimental results on running the quantum verification circuit displayed in Fig. 2 for 1024, 4096, and 8192 shots.*

Number of shots employed	Measurement probability of |0⟩ state (%)	Measurement probability of |1⟩ state (%)
Experimental		
1024	92.87	6.12
4096	93.53	6.47
8192	93.34	6.65
Simulation	100.00	0.00

3. CONCLUSION

Forgery of a cheque transaction can be made almost impossible by using the technology of quantum currency. A quantum cheque transaction uses quantum computers, which run on qubits, the critical components of data manipulation. As qubits can exist in two states simultaneously called quantum superposition, observing a qubit is impossible. Hence, the cheque transaction performed by quantum computers is extremely secure. In this paper, we successfully designed quantum circuits for the two-key process in the quantum cheque transaction, namely quantum cheque generation and quantum cheque verification. The computational experiments were conducted to verify the accuracy of the designed circuits. The obtained results were compared with the simulated results to measure accuracy.

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Differentiating Potentially Malicious Darknet Traffic from Benign Network Traffic Using Machine Learning

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ABSTRACT

This paper uses a systematic approach to assess the capability of machine learning algorithms to be employed for analyzing, testing, and evaluating network traffic. A Darknet is a subnet of the Deep Web that consists of unused internet address space where there are no legitimate, active servers or hosts. Therefore, traffic originating from there is deemed potentially malicious. Tracing communications remains a challenge because the dark web is a decentralized network that is accessed through anonymous proxy networks such as the Tor browser. However, the network traffic from our dataset can be used to predict whether traffic is from the Tor browser. This paper presents a binary-classifying approach to distinguishing darknet traffic from benign traffic by analyzing the flow of network packets using machine learning algorithms. The machine learning model differentiates darknet traffic from benign traffic and flags any traffic that comes from an IP address within the Tor browser as potentially malicious activity. Our dataset provides us with various features containing information about the traffic: source & destination ports/IP's, protocols, flow durations, forward/backward packets data, etc., to distinguish malicious darknet traffic from regular benign activities. The capability of machine learning classifiers is evaluated considering their accuracy, precision, recall, and F-score, confusion matrices, ROC curves, and feature importance.
Key Words: machine learning algorithms, anonymous proxy networks, network packets

1. INTRODUCTION

The unused internet address space that is the "Darknet" is not meant to receive network traffic and thereby packets that flow through it are viewed as suspicious. This traffic could contain all sorts of malicious network activity such as network scanning [1] (the process of analyzing network packets for exploitation), keylogging (malicious software that records everything typed on a system including personal information or credentials [2]), RAT's (Remote Administration Tools that allows a host to take complete control over another system) and other malwares.

In this paper, a systematic approach is proposed to evaluate the capability of machine learning algorithms to be employed for analyzing, and detecting malicious traffic related to darknet. Our traffic monitoring models constructed based on two machine learning models, extra trees classifiers and random forest classifier, to analyze the dataset and predict whether traffic will be deemed potentially malicious or benign based on the flow of its network packets and other networking features specified for darknet traffics. Canadian Institute for Cybersecurity (CIC) has released an ISCXTor2016 dataset [4] that includes darknet traffics. The paper utilizes the IBM platform, AutoAI, to analyze our darknet data and select the optimal ML algorithms based on efficiency and accuracy [3].

2. DATASET TRAINING AND TESTING

The generated data that was used for our experiment was adopted from the ISCXTor2016 dataset in a CSV file. [4] The data was collected by capturing snapshots of network flows that contain benign traffic along with traffic that originated in the Tor. The traffic features in our dataset are described in Table 1. There is a total of 29 features that collectively give us a statistical view of our traffic flows. These features are analyzed by IBM AutoAI to construct an ML model that will predict the source of a flow, whether benign or potentially malicious.

Table 1. *List of 29 statistical features extracted from captured traffic*

Source IP	IP address of sending device
Soure Port	port numer of sending device
Destination IP	IP address of receiving device
Destination Port	port number of receiving device
Protocol	IP version
Flow Duration	duration of a packet stream
Flow Bytes/s	number of flow bytes per second
Flow Packet/s	number of flow packets per second
Flow IAT Mean	mean time between two packets sent in the flow
Flow IAT Std	standard deviation time between two packets sent in the flow
Flow IAT Max	maximum time between two packets sent in the flow
Flow IAT Min	minimum time between two packets sent in the flow
Fwd IAT Mean	mean time between two packets sent in the flow
Fwd IAT Std	standard deviation time between two packets sent in the flow
Fwd IAT Max	maximum time between two packets sent in the forward direciton
Fwd IAT Min	minimum time between two packets sent in the forward direction
Bwd IAT Mean	mean time between two packets sent in the backward direction
Bwd IAT Std	standard deviation of two packets sent in the backward direction
Bwd IAT Max	maximum time between two packets sent in the backward direction
Bwd IAT Min	minimum time between two packets sent in the backward direction
Active Mean	mean time a flow was active before becoming idle
Active Std	standard deviation time a flow was active before becoming idle
Active Max	maximum time a flow was active before becoming idle
Active Min	minimum time a flow was active before becoming idle
Idle Mean	minimum time a flow was idle before becoming active
Idle Std	standard deviation time a flow was idle before becoming active
Idle Max	maximum time a flow was idle before becoming active
Idle Min	minimum time a flow was idle before becoming active
Label	label

AutoAI splits our data into 2 datasets: a training dataset as well as a testing dataset. The training data is used for the training of our machine learning algorithm, and the testing data is used to test the performance metrics of the newly constructed ML models such as predictive accuracy, precision, Area Under the receiver operating characteristic (ROC), etc. AutoAI then compares various machine learning algorithms such as Decision Tree Classifier, Extra Trees Classifier, Gradient Boosting Classifier, LGBM Classifier, XGB Classifier & Random Forest Classifier using a portion of the dataset. AutoAI chooses the best two promising ML algorithms and generates pipelines for the models. For each ML algorithm, AutoAI generates each of the following pipelines: automated model selection (Pipeline 1), hyperparameter optimization (Pipeline 2), automated feature engineering (Pipeline 3), 2nd hyperparameter optimization (Pipeline 4). Our testing data is also used to generate a confusion matrix for each model pipeline. The confusion matrices compare our model's predictions to the actual data results. Figure 1 shows our training progress. Our dataset is first analyzed, then split into training/testing data, then preprocessed, which ultimately allows our model to select the best machine learning algorithm for our data.

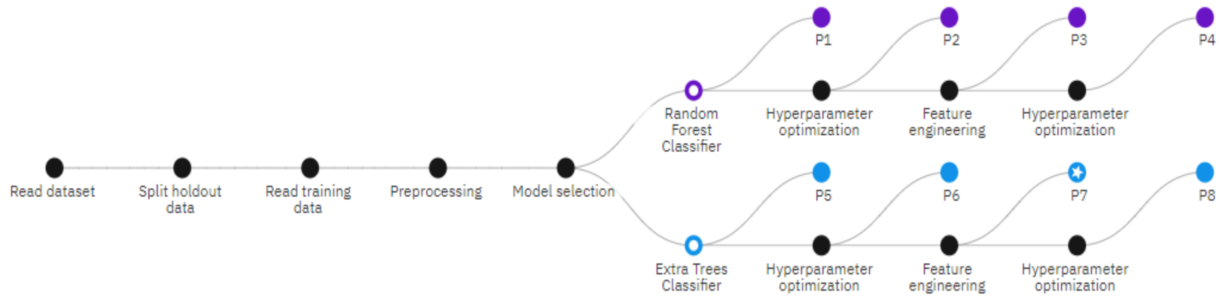

Figure 1. Training progress pipelines for two optimal ML algorithms.

3. RESULTS

Our ML model evaluates and cross-validates the six machine learning algorithms on our dataset and applies the algorithms that best match our data and prediction type. The classification metrics of the Extra Trees Classifier algorithm, as well as the Random Forest Classifier, are selected by our model as the algorithms to be used to differentiate our traffic data. Our model evaluates the two ML algorithms and collects measurements from both for the following performance metrics for each pipeline: accuracy, precision, recall, area under ROC curve, F-Score, average precision, and log loss. Precision and recall are measured by comparing the predicted results of the training data to the actual results in the testing data and finding the success rate of differentiation. F-Score is measured by the balance of both precision and recall as both metrics share an inverse relationship. The ideal F-Score would be 1, which would represent the best possible accuracy, whereas a score of 0 represents the worst possible accuracy. Log loss is used to measure the uncertainty (also known as entropy) of our model, which can be used to determine probabilistic outcomes for data beyond just our dataset. [5] The AUC ROC (area under the receiver operating characteristic curve) is displayed in a graph that depicts the true positive rate (correctly-predicted positive outcomes) against the false positive rate (falsely-predicted negative outcomes). Each performance metric reports cross-validation as well as a holdout during binary classification. The cross-validation allows us to evaluate better how our algorithms will perform on other data, whereas the holdout just helps us evaluate our own data. Our model also constructs a confusion matrix for each pipeline that tells us exactly how many packet streams were accurately predicted. Feature importance is also taken into account by our ML algorithms to give a visual of the usefulness of each feature to our predictive algorithms.

3.1. EXTRA TREES CLASSIFIER

The extra trees classifier is an averaging machine learning algorithm that is based on randomized decision trees. [6] Multiple decision trees are aggregated to generate the algorithm's predicted output. This algorithm provided our ML model with our top-performing pipeline, Pipeline 7, which has been enhanced with Hyperparameter Optimization (HPO-1) and Feature Engineering (FE). Also, Pipeline 8, which has the same enhancements with just a 2nd Hyperparameter Optimization (HPO-2) for a deeper refinery. The output data for both pipelines are identical, and they both have perfect predicting accuracy. You can see the evaluation metrics in Figure 2(a). Here we see the accuracy, area under ROC curve, precision, recall, F-score, and average precision of Pipeline 7 have all been calculated with perfect accuracy for both the cross-validation and the holdout. You can also see that our log loss for both evaluations has an extremely low level of uncertainty. The holdout is having a log loss score of 0.001, and the cross-validation is having a score of 0.002. Because of the perfect accuracy of this pipeline, our ROC curve has a slope of 0 at 100% in Figure 2(b). In Figure 2(c), we can see the confusion matrix for this pipeline. As you can see, our true positives and true negatives were predicted with virtually perfect accuracy. Only one potentially malicious darknet packet stream out of almost 1500 managed to get past our enhanced algorithm without being flagged. Despite the one mishap in distinguishing darknet traffic in our dataset, our pipeline managed to not flag any benign traffic as suspicious. Feature importance is used to show us the relevance of each of our features to the accuracy of the algorithm's predictions. The Feature Engineering (FE) enhancement added to Pipeline 7 & 8 allowed our algorithm to generate new features using our original features to help strengthen performance. Twenty new features were added to our dataset as a result of this enhancement. Our most important features are shown in Figure 2(d), they include: Protocol, NewFeature_15 (*sin(square(SourceIP))*), NewFeature_10 (*sin(sourceIP)),* NewFeature_17 (*sin(square(DestinationIP))*), flow duration and source IP. These features, along with others, had high relevance in our ML algorithm.

3.2. RANDOM FOREST CLASSIFIER

The random forest classifier constructs multiple decision trees using averages. It supports both binary classifications as well as categorical features [6]. The algorithm creates a set of decision trees and aggregates different decision trees to generate the algorithm's predicted output. [3] The top two performers for this algorithm have perfect accuracy as well. Pipeline 3, similarly to Pipeline 7, was enhanced with Hyperparameter Optimization (HPO-1) and Feature Engineering (FE). Likewise, Pipeline 4, similarly to Pipeline 8, has the same enhancements with just a 2nd Hyperparameter Optimization (HPO-2). Also similar to Pipelines 7 & 8, Pipelines 3 & 4 have identical output data as well. If we look at Figure 3(a), we can see the perfect evaluation scores across the board for Pipeline 3, just like in our extra trees algorithm. Our log loss is also extremely low for this algorithm as well, with our holdout having a log loss of 0.001 and our cross-validation having a log loss of .003. Our ROC curve is perfect again for this algorithm, as shown in Figure 3(b). If we look at the confusion matrix in Figure 3(c), this time two packet streams were predicted inaccurately. Our random forest classifier failed to flag a potentially malicious packet stream and, additionally, this time inaccurately flagged one benign packet stream out of almost 7000 as suspicious. However, that rate is still virtually perfect. Despite the high accuracy, the Feature Engineering (FE) enhancement for the random forest algorithm utilized our features quite differently than the enhancement in the extra trees algorithm. While still generating 20 new features, the random forest algorithm-generated different new features than those in different trees. In Figure 3(d), we see our most important features include: NewFeature_8 (*nxor(DestinationPort, SourceIP)*), Bwd IAT Std, Fwd IAT Std, NewFeature_3 (*nxor(SourceIP, DestinationPort)*), NewFeature_10 (*nxor(DestinationPort, DestinationIP)*) and source IP.

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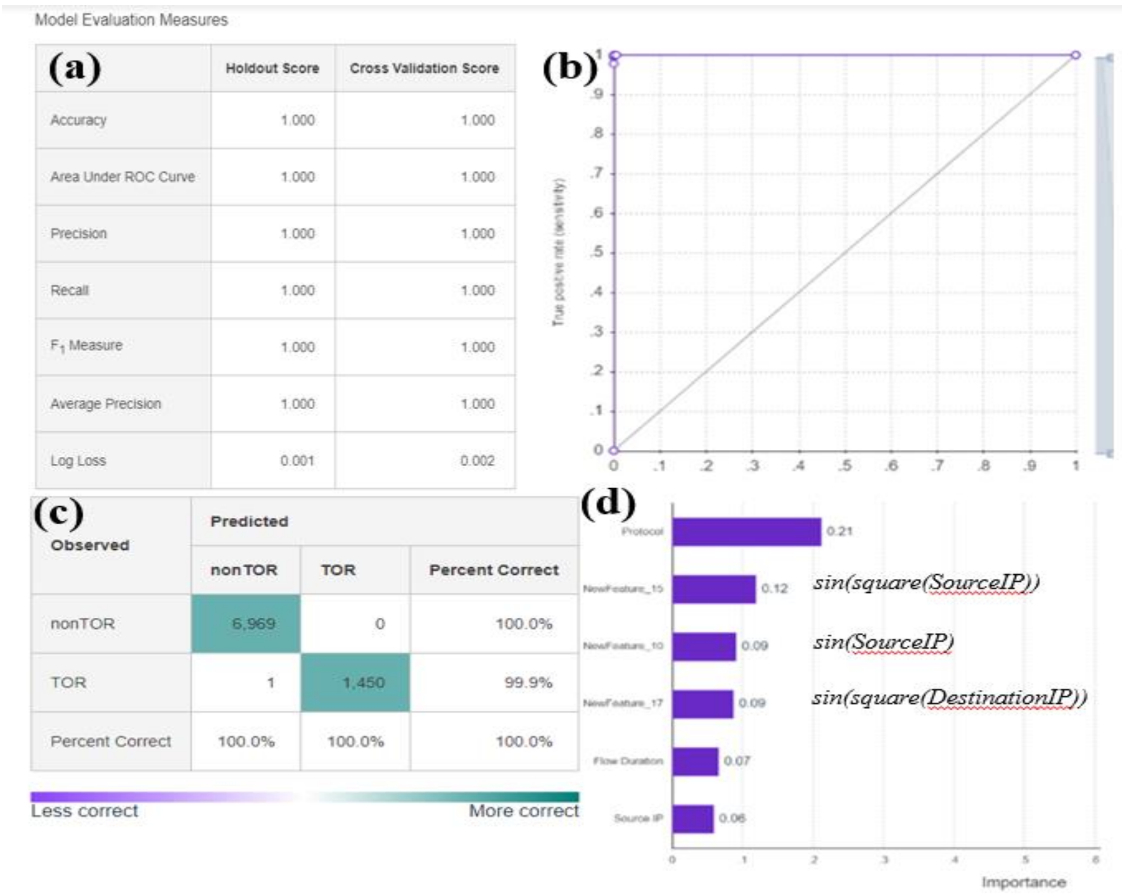

Model Evaluation Measures

(a)	Holdout Score	Cross Validation Score
Accuracy	1.000	1.000
Area Under ROC Curve	1.000	1.000
Precision	1.000	1.000
Recall	1.000	1.000
F_1 Measure	1.000	1.000
Average Precision	1.000	1.000
Log Loss	0.001	0.002

(c) Observed	Predicted		
	nonTOR	TOR	Percent Correct
nonTOR	6,969	0	100.0%
TOR	1	1,450	99.9%
Percent Correct	100.0%	100.0%	100.0%

Figure 2. Extra Trees Classifier results (a) model evaluation (b) ROC curve (c) confusion matrix (d) feature importance

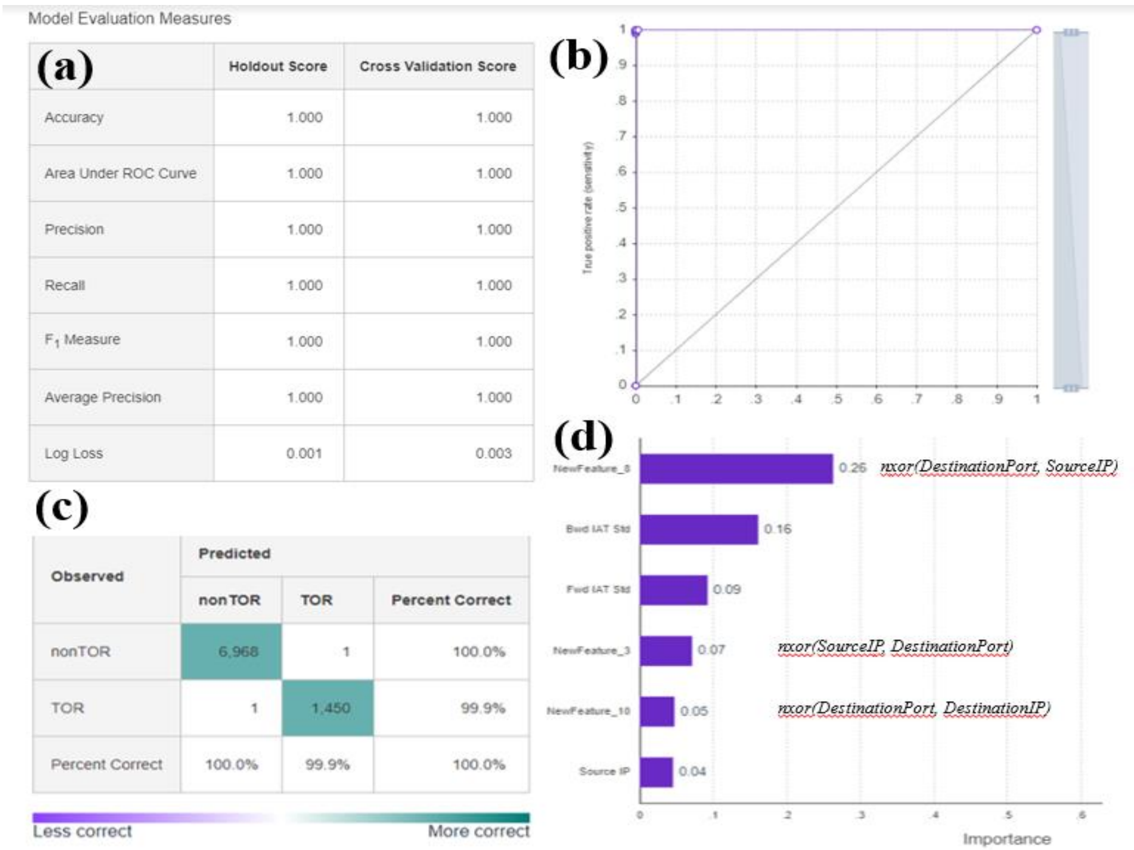

Figure 3. Random Forest Classifier results (a) model evaluation (b) ROC curve (c) confusion matrix (d) feature importance.

4. CONCLUSION

This paper has presented a systematic approach to assessing and evaluating the capability of machine learning algorithms to be employed for analyzing, testing and evaluating network traffic using ML models. We managed to successfully develop a model that could accurately distinguish suspicious darknet traffic from benign network traffic so that we could flag potentially malicious activity. Our model analyzed our dataset so that it could evaluate and cross-validate the six machine learning algorithms and find the best algorithm for our experiment. The results tell us that the Extra Trees and Random Forest machine learning algorithms managed to both reach a binary classification accuracy of 100%, with each of its optimal pipeline's performance metrics being virtually perfect. The performance was measured using accuracy, precision, ROC curve, recall, F-Score, confusion matrices, and feature importance. Our extra trees confusion matrix shows us only one potentially harmful packet stream out of almost 1500 managed to not get flagged, and our random forest confusion matrix shows us one unflagged potentially malicious packet stream, as well as one benign packet stream out of almost 7000 being inaccurately flagged also. For our Extra Trees algorithm, Protocol was our most important feature significantly, followed by *sin(square(SourceIP))*. For our Random Forest algorithm, *nxor(Destination Port, Source IP)* was our most important feature significantly, followed by Bwd IAT Std (standard deviation of two packets sent in backward direction). These features each played an essential role in our binary-classifying approach.

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Intergenerational Continuity of Adverse Childhood Experiences across Generations

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ABSTRACT

Emerging research has documented the continuity of ACEs between generations of parents and their children. This study examined the intergenerational continuity of ACEs specifically between college students and their primary caregivers. Out of the entire sample of 463 college students from the University of Louisiana at Lafayette who responded to an online survey, 152 of them recruited their primary caregivers to respond to the survey. The survey included the Adverse Childhood Experience scale—a 10-item scale assessing an individual's recall of all adverse experiences that occurred prior to his/her eighteenth birthday. The results indicated that, when college students were matched with their primary caregivers, their ACEs scores were not different from those of their caregivers. This supports the findings of past research that identified the continuity of ACEs across generations. Understanding this continuity can help implement intervention programs that can break the cycle of ACEs and their impacts on general well-being.

1. INTRODUCTION

Adverse Childhood Experiences (ACEs) are defined as traumatic experiences that occurred in a child's life before the age of eighteen. These experiences include categories that assess emotional, physical, and sexual abuse; mental illness, substance abuse, criminal behavior in the household, or violence against their mother (Felitti et al., 1998). Previous literature has shown that these experiences can be passed down through generations from a child's primary caregiver (Perry & Pollard, 2018). A majority of adults in the United States have reported at least one negative childhood experience before they reached adulthood (Woods-Jaeger et al., 2018). The literature confirms that not only can the report of the experiences be passed down through generations, but the effects of ACEs can have an even more significant effect on the next generation. Children exposed to ACEs may experience heightened stress responses, insecure attachments to their caregivers, and somatic symptoms (Choi et al., 2020; Cooke et al., 2019; Corcoran & McNulty, 2018). Emotional and behavioral issues have been observed in children, who experienced ACEs, in which they disrupt the attachment bond with the primary caregiver (Choi et al., 2020). Furthermore, the presence of constant dysfunction has been found to have a strong impact on mental health later in life (Edwards, Anda, Felitti, & Holden, 2003).

This leads to the conclusion that caregivers' adverse experiences likely have a larger impact on their children than originally thought.

The purpose of this study was to examine the intergenerational continuity of ACEs between generations, specifically between college students and their primary caregiver. Previous studies showed that ACEs have a continuity effect across generations, so this study expected to observe the same patterns.

2. METHOD

2.1 Participants and Procedure

This study recruited 463 college students (328 females, M_{age} = 20.1, SD_{age} = 3.9) via the SONA participant recruitment system of the Psychology Department at the University of Louisiana at Lafayette. Students were instructed to go to the Psychology Department Computer Laboratory to participate in an online survey. Participation was voluntary, but participants were rewarded extra credits to partially fulfill research requirements for the courses in which they were enrolled. Once students completed the survey, they were offered extra credits if they helped recruit their primary caregiver to also participate in the study via email, a physical copy of the study, or schedule an appointment with the computer lab. The primary caregivers were identified by the college students as the most important people during their first eighteen years of life. Out of the entire college sample, 152 students (110 females, M_{Age} = 20.1, SD_{Age} = 4.0) recruited their primary caregiver (132 females, M_{age} = 49.9, SD_{age} = 8.4) to respond to the survey. The data of the 152 students and their caregivers were matched for subsequent analyses.

2.2 Measures

Adverse Childhood Experience. The Adverse Childhood Experience (ACE; Dong et al., 2004; Felitti et al., 1998) scale is a 10-item self-report questionnaire used to examine an individual's recall of adverse experiences that occurred prior to his/her eighteenth birthday. These adverse events pertain to an individual's personal experience of emotional abuse, physical abuse, sexual abuse, emotional neglect, physical maltreatment and/or neglect, parental separation/divorce, family substance use, mental illness with the household, and/or parental incarceration. Each of the items had answer options of 'Yes' or 'No'. For each item, a 'Yes' response signifies an individual item score of one. The scoring process of ACEs were conducted by summing all of the 'Yes' responses from the 10-items; therefore, an individual's ACE score ranged from 0 to 10. A score of '0' indicated that the individual experienced no adversities during childhood. According to Dong et al. (2004), an ACE score from 1 to 3 is considered as a low occurrence of adverse events, an ACE score of 4 indicates a moderate level of traumatic events, and an ACE score of 5 or more is considered a high level of occurrence of adverse events. An exemplar item referring to an experience of physical neglect states "*Did you often or very often feel that (1) no one in your family loved you or thought you were important or special or (2) your family did not look out for each other, feel close to each other, or support each other?*" An exemplar item pertaining to mental illness within the immediate family states, "*Was a household member depressed or mentally ill, or did a household member attempt suicide?*" The Cronbach's alpha for the ACEs scale in the current study was .75.

3. RESULTS

3.1 Descriptive Statistics

Collapsing the college students and the primary caregivers, the average ACE score for the entire sample was 1.84 (*SD* = 1.93) with missing data values (*N* = 593). From the sample, approximately 68.5% of the participants reported at least 1 ACE; 44.9% reported at least 2 ACEs; 30.4% reported at least 3 ACEs; 19.8% reported at least 4 ACEs; and 11.2% of participants reported 5 or more ACEs.

When treating the two generations as two independent groups, college students (M_{ACE} = 1.99, SD_{ACE} = 1.96) reported significantly more ACEs than their caregivers (M_{ACE} = 1.37, *SDACE* = 1.65), according to a Welch's *t*-test, $t = 3.76$, $p < .001$ (Welch's *t*-test). When the 152 students were matched with their caregivers, the average ACE score of 152 college students (M_{ACE} = 1.69, SD_{ACE} = 1.80) did not differ from the average ACE score of their matched, respective caregivers (M_{ACE} = 1.37, SD_{ACE} = 1.65), $t = 1.54$, $p = .937$. However, when individual items were examined, the 152 college students reported higher scores on 'emotional neglect', $t = 2.86$, $p = .003$, and 'battered mother', $t = 2.62$, $p = .005$, after Bonferroni Correction.

Correlation analysis showed that ACE scores of the matched generations were correlated $r = .21$, $p = .014$. Individual item examinations indicated that there were significant correlations between the two generations for 'sexual abuse', $r = .40$, $p < .001$, 'mental illness in household', $r = .18$, $p = .036$, and 'substance use in household', $r = .19$, $p = .024$.

4. DISCUSSION

This study examined the intergenerational continuity of ACEs. After examining the results, college students reported higher numbers of ACEs than those of their caregivers. However, when the college students were paired with their primary caregivers, their ACEs scores mirrored those of their caregiver, showing a continuity effect. These results align with those of previous findings in that ACEs in one generation are related to the ACEs in the next generation, and the lasting impacts of ACEs on caregivers will have relevance in the mental and physical outcomes of their children (Edwards et al., 2003; Lê-Scherban et al., 2018; Schofield et al., 2018; Woods-Jaeger et al., 2018). The results also showed that the ACEs of college students were significantly related to those of their caregivers, supporting the idea of intergenerational continuity of ACEs across generations. These findings have further implications for the implementation of intervention programs that work to break the intergenerational cycle of childhood adversity.

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Differences in Adverse Childhood Experiences, Attachment Insecurity, and Their Association between Two Generations

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ABSTRACT

Prior research has identified the relations between adverse childhood experiences (ACEs) and attachment insecurity. However, the literature is limited regarding the intergenerational continuity of the relation between ACEs and attachment. Learning more about how childhood trauma transmits across generations is important to begin developing intervention methods to break the cycle of these experiences. This study sought to examine the individual differences in ACEs and attachment insecurity and their associations between two generations. A sample of 463 college students participated in an online survey, who were then prompted to decide whether to help recruit their primary caregiver. The online survey included items from the (1) Adverse Childhood Experiences Scale, assessing traumatic events that occurred before the age of 18 and the (2) Experience in Close Relationships scale, examining adult internal working models with items representing two subscales: attachment anxiety and attachment avoidance. The results showed a continuity of ACEs between generations in that students' and caregivers' scores did not differ, but students scored significantly higher in attachment insecurity than their caregivers. ACEs were also only related to attachment anxiety in college students. These findings suggest a developmental difference between college students' perception of their ACEs than that of their caregivers.

1. INTRODUCTION

Adverse childhood experiences are traumatic events that occur in the first 18 years of an individual's life and include categories such as emotional, physical, and sexual abuse; mental illness, substance abuse, criminal behavior in the household, or violence against their mother (Felitti et al., 1998). Children exposed to ACEs scores can develop a heightened stress response which disrupts the normal development of emotion regulation, physical health, and attachment to their caregiver. (Choi et al., 2020; Corcoran & McNulty, 2018). Additionally, ACEs can disrupt the attachment bond between the child and the primary caregiver, which has been shown to predict childhood behavioral and emotional issues (Choi et al., 2020).

Attachment insecurity is a type of insecurity that results from inconsistent, neglectful, abusive and uncontrolled caregiving methods (Shilkret & Shilkret, 2011). Attachment insecurity is categorized into two major dimensions: attachment anxiety and attachment avoidance. Anxiety is characterized by the fear of being abandoned or rejected in relationships, and avoidant is characterized by a fear of interpersonal relationships and closeness (Brennan et al., 1998).

Attachment style and ACEs of the caregiver has been shown to have a direct link to behavioral and emotional problems in their children (Cooke et al., 2019). Prior research has presented the relations between adverse childhood experiences (ACEs) and attachment insecurity, specifically attachment anxiety (Lin et al., 2020). However, there is limited research examining the intergenerational continuity of ACEs in relation to attachment insecurity, particularly involving a sample of college students, which this study sought to examine.

2. Method

2.1 Participants and Procedure

This study recruited a sample of college students and their primary caregivers who were identified by the college students as the most important person during their first eighteen years of life. There were 463 college students (M_{age} = 20.1, SD_{age} = 3.9) who were recruited through the Psychology Department SONA system. Students were given instructions to go to the Psychology Department computer lab to complete the survey and were informed that the survey should take approximately one hour. The students were also informed of the voluntary nature of the study. Students who chose to voluntarily participate were given the option to recruit their caregiver, who were immediately contacted via email after the students completed the survey.

Out of the entire college sample, 152 students (110 females, *M*age = 20.1, *SD*age = 4.0) invited their primary caregivers (132 females, M_{age} = 49.9, SD_{age} = 8.4) to respond to the survey. Caregivers had the option of either 1) completing the survey at their leisure through an email with the survey link, 2) completing the survey on paper through a letter sent to their physical address, or 3) by scheduling an appointment to complete the survey in the Computer Lab. The data of the 152 students and their caregivers were matched for subsequent analyses.

2.2 Measures

Demographic Information Form. This form was given to both students and caregivers, The questions asked for information pertaining to age, ethnicity, gender identity, classification, socioeconomic status, relationship status, and educational level. Students were also asked to report on their caregiver's relationship status, highest educational level, and occupational status.

Adverse Childhood Experiences. The Adverse Childhood Experiences scale (Dong et al., 2003; Felitti et al., 1998) is a 10-item questionnaire that is used to assess an individual's recall of adverse childhood experiences before the age of eighteen. These questionnaire items ask about an individual's adverse childhood experiences pertaining to emotional neglect, emotional and physical abuse, sexual abuse, physical maltreatment, neglect, family substance abuse, divorce or separation, living with someone with a mental illness, and parental incarceration. Two answer options of "Yes" or "No" were given for each question. An exemplar question referring to mental illness within the household states *"Was a household member depressed or mentally ill, or did a household member attempt suicide?"* An answer of "Yes" indicated a score of one point, and an answer of "No" indicated a score of zero points. The scoring of the ACEs scale consists of summing the score of each item; therefore, an individual's score ranges from 0-10. The Cronbach's alpha for the ACEs scale in the current study was .75.

Experience in Close Relationships Scale (ECR)- Short Form. The Experience in Close Relationship Scale –Short Form (ECR-SF; Wei, Russell, Mallinckrodt, & Vogel, 2007) is a short version of designed to assess adult internal working models. This short form scale contains two subscales of attachment insecurity: attachment anxiety and attachment avoidance. The Anxiety subscale (6 items) measures fear towards interpersonal rejection or abandonment. An exemplar item from the anxiety subscale states “I need a lot of reassurance that I am loved by my partner”. The Avoidance subscale (6 items) measures the fear of dependence and interpersonal closeness. An exemplar item from this subscale states “I want to get closer to my partner, but I keep pulling back”. Using a Likert-type scale, participants reported the extent to which they agreed or disagreed with the items, 1 (*disagree strongly*) to 7 (*agree strongly*). Higher levels of attachment insecurity were determined by higher scores on the two subscales. The Cronbach’s alphas for the ECF-SF Anxiety and Avoidance subscales were .75 and .78, respectively.

3. Results

3.1 Correlations

Matched-pairs *t*-tests were performed to examine the generational differences. The results indicated that the average ACE score of college students (M_{ACE} = 1.7, SD_{ACE} = 1.8) did not differ from that of their caregivers (M_{ACE} = 1.4, SD_{ACE} = 1.7), t = 1.54, p = .937. Also, ACE scores of the two generations were positively correlated with each other, r = .21, p = .014.

In contrast, college students reported higher levels of attachment anxiety ($M_{Anxiety}$ = 24.9, $SD_{Anxiety}$ = 1.80) and attachment avoidance ($M_{Avoidance}$ = 16.1, $SD_{Avoidance}$ = 6.8) than those of their caregivers ($M_{Anxiety}$ = 16.0, $SD_{Anxiety}$ = 6.7; $M_{Avoidance}$ = 13.8, $SD_{Avoidance}$ = 5.9), t = 6.86, p < .001, and t = 2.18, p = .02, respectively. Correlations between the two generations were nonsignificant for attachment anxiety and avoidance, respectively.

For college students, ACEs positively predicted attachment anxiety, r = .41, p < .001, but not avoidance. For caregivers, ACEs did not predict either attachment anxiety or avoidance. Attachment avoidance in caregivers was significantly associated with attachment anxiety in students, r = .52, p < .0001.

4. Discussion

This study sought to compare the levels of ACEs and attachment insecurity between two generations while also contrasting the generation-specific associations between the two constructs. First, when the two generations were compared based on ACEs, caregivers and students showed no difference in their scores. Second, the ACEs scores of the two generations were correlated with each other. These results suggested continuity of ACEs between the two generations. The results on each of the two dimensions of attachment insecurity, however, did not reveal continuity across the two generations. College students showed higher levels of both anxiety and avoidance, which were independent of their caregivers’ anxiety and avoidance, respectively. Differential associations of ACEs with attachment insecurity were found between the two generations. ACEs were related to attachment anxiety only in college students, but not their caregivers. ACEs were not related to attachment avoidance at all in both college students and their caregivers. The findings may be explained by the socioemotional selectivity theory (Reed & Carstensen, 2012) in that older individuals tend to focus on more positive aspects of their life, as compared to students. As a result, the older generation might perceive less fear towards either interpersonal rejection or interpersonal closeness—characteristics of lower levels of attachment insecurity. The results underscored a developmental change in the link between ACEs and attachment insecurity (particularly attachment anxiety), with the older generation showing lessened negative effects of ACEs.

Although each of the two dimensions of attachment insecurity did not show continuity between the two generations, attachment avoidance in primary caregivers was associated with anxious working models in their children. It was likely that avoidant caregivers tended to show insufficient levels of warmth and affection to support the development of emotional security in their children (Bowlby, 1969; Cummings & Davies, 2011). Thus, children of avoidant caregivers might develop fear towards abandonment or rejection.

The findings of this study addressed the issue of continuity of ACEs and attachment insecurity between two generations. These findings carry implications for formulating prevention and intervention programs to mitigate the adverse effects of childhood adversity.

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Childhood Adversity and Well-being: Differences between College Students and Their Primary Caregivers

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ABSTRACT

Research has shown that events experienced in childhood can create an impact on overall wellbeing; however, cross generational effects of this impact have remained unclear. Understanding the relation between adverse childhood experiences (ACEs) and wellbeing within and across generations is an important to improving mental and physical health outcomes. A sample of 463 college students and primary caregivers of 152 students of the sample took part in an online survey that included: (1) the Adverse Childhood Experiences scale, examining adverse events that occurred prior to the individual's eighteenth birthday, (2) The Depression Anxiety Stress Scales, evaluating current levels of depressive symptoms, stress, and anxiety, and (3) Somatization Scale of the Symptom Checklist, assessing somatic symptoms. The results of the study revealed that college students reported higher levels of depression, anxiety, stress, and somatic symptoms compared to their respective caregivers. However, the ACEs scores did not show a significant difference. Moreover, ACEs reported by college students were significantly correlated with depression, anxiety, stress, and somatic symptoms while the scores for their caregivers did not. The findings carry implications for generation-specific approach for addressing the impacts of ACEs on well-being.

1. INTRODUCTION

Previous studies have documented the connections between adverse childhood experiences and health outcomes later in life (e.g., Anda, Tietjen, Schulman, Felitti, & Croft, 2010; Felitti et al., 1998). Adverse childhood experiences (ACEs) are traumatic experiences that occur prior to an individual turning 18 and include the following categories: physical, emotional and sexual abuse, emotional and physical neglect, and being exposed to violence against an intimate partner or mother (Feliti et al., 1998). ACEs have been shown to be related to depression (Vibhakar, Allen, Gee, & Meiser-Stedman, 2019), anxiety (Makriyianis et al., 2019), and stress (Makriyianis et al., 2019) and somatic symptoms (Hart et al., 2013).

Recently, research has pointed to the continuity of ACEs between parents and their children (e.g., Schofield et al., 2018). Parents' experiences of ACEs may impact the number and severity of ACEs (Woods-Jaeger, 2018), which has relevance in morbidity and mortality and some health behaviors (Lê-Scherban, 2018). Understanding how ACEs transmit from one generation to another is important to promoting resilience among parents and children exposed to ACEs. However, there has been scarce information on the differences in the associations of ACEs with health outcomes across generations. This study sought to, first, describe the continuity of ACEs across generations; second, examine if there were differences in the mental and physical symptoms between the generations, and third, compare and contrast the associations of ACEs with depressive, anxiety, stress, and somatic symptoms across the two generations.

2. METHOD

2.1. Participants and Procedure

A sample of 463 college students (328 female, M_{age} = 20.06, SD_{age} = 3.92) responded to an online survey. Students were recruited through the SONA system of the Psychology Department at the University of Louisiana at Lafayette. The study was approved by the Institutional Review Board at the University. Participants were informed of the voluntary nature of the study. Students who chose to voluntarily participate were given the option to recruit their caregivers, who were immediately contacted via email by the researchers after the students completed the survey.

Out of the entire college student sample, 152 students (110 females, M_{Age} = 20.1, SD_{Age} = 4.0) invited their primary caregivers (132 females, M_{age} = 49.86, SD_{age} = 8.41) to participate in the study. The primary caregivers were identified by the 152 students as the most important individuals assuming the roles of parenting during the students' first eighteen years of life. The data of the 152 students and their caregivers were matched for subsequent analyses.

2.2. Measures

Adverse Childhood Experience. The Adverse Childhood Experience (ACE; Dong et al., 2003; Felitti et al., 1998) scale is a 10-item self-report questionnaire used to assess the adverse experiences which occurred prior to an individual's eighteenth birthday. These adverse experiences include an individual's personal history of emotional abuse, physical abuse, sexual abuse, emotional neglect, physical maltreatment and/or neglect, parental separation/divorce, family substance use, mental illness with the household, and/or parental incarceration. Each of the items solicits either a 'Yes' or 'No' response. For every "Yes" response, the individual item score is one; for every "No" response, the score is zero. Standard items that would be asked of the individual included but were not limited to items like "Were your parents ever separated or divorced?" and "Did a household member go to prison." The ACE score is the sum of the scores of the 10 items. Therefore, an individual's ACE score can range from 0 to 10. The Cronbach's alpha for the ACEs scale in the current study was .75.

The Depression Anxiety Stress Scale. The Depression Anxiety Stress Scale (DASS, Lovibond & Lovibond, 1995) is a 21-item scale which evaluates the symptoms of depression, anxiety, and stress. A 4-point Likert scale is utilized for participants to report the occurrence of symptoms of depression, anxiety, stress ranging from 0 (*never*), 1 (*sometimes*), 2 (*often*), and 3 (*almost* *always*). Standard items of the subscales included "*I was unable to become enthusiastic about anything*" for depression, "*I felt I was close to panic*" for anxiety, and "*I found it difficult to relax*" for stress. The Cronbach's alphas for the Depression, Anxiety, and Stress subscales were .90, .81, and .82, respectively.

Somatization Scale of the Symptom Checklist Revised. The subscale of the Somatization Scale (12 items) of the Symptom Checklist Revised (SCL-90-R, Derogatis, 1994, 12-item) is a self-report measure which assesses 12 somatic symptoms caused psychological pain or distress in the past 7 days. The 12 somatic symptoms. The items are responded on a 5-point scale ranging from 0 (*Not at All*) to 4 (*Extremely*) in regard to the extent to which each item describes the respondent's somatic symptoms in the past 7 days. Exemplar items from the subscale include, "*Feeling weak in parts of your body,*" and "*Pains in heart or chest.*" The Cronbach's alpha for the SCL-90-R somatic subscale for this study was .88.

3. RESULTS

3.1 Generational Differences in the Study Variables

The results of matched-pairs-*t*-tests indicated that the average ACE score of college students (M_{ACE} = 1.7, SD_{ACE} = 1.8) did not differ from that of their caregivers (M_{ACE} = 1.4, SD_{ACE} = 1.7), t = 1.54, p = .937. However, college students reported higher scores on depression, anxiety, stress, and somatic symptoms than their matched primary caregivers (after Bonferroni Correction), t = 6.30, $p < .001$, t = 5.65, $p < .001$, t = 5.47, $p < .001$, and t = 4.11, $p < .001$, respectively.

3.2 Generational Correlations of the Study Variables

ACES of the two generations were significantly correlated with each other, r = .21, p = .014. However, depressive symptoms of the two generation did not correlate with each other; the similar non-significant correlational pattern applied to anxiety, stress, and somatic symptoms between the two generations.

3.3 Associations of ACEs with Health Outcomes

ACEs reported by college students were significantly correlated with all of the depression, anxiety, stress, and somatic symptoms, r = .37, $p < .001$, r = .30, $p < .001$, r = .27, p = .003, and r = .33, $p < .001$, respectively. However, ACEs reported by caregivers did not correlate with any of their mental and physical symptoms. Notably, ACEs of the older generation did not relate to any of the college students' psychological or somatic symptoms.

4. DISCUSSION

The purpose of the study was to examine if there was continuity of ACEs across generations. The ACEs scores from both college students and their caregivers exhibited that the amount of ACEs reported by the caregiver was not different from that of the child. As well, ACEs scores from the two generations were correlated with each other, suggesting the intergenerational continuity. This creates speculation if the primary caregiver is creating a particular pattern that they themselves experienced growing up and projecting that onto their children. There was a study done by Woods-Jaeger et al. (2018), in which they interviewed parents who had previously experienced multiple adverse childhood experiences regarding their personal account and how their experiences were potentially projected upon their own children. The results showed that the ACES that the parent had endured had long lasting effects on mental and physical well-being and that the transmission of the experiences turned into a cycle upon that next generation of the children.

College students reported more symptoms of depression, anxiety, stress, and somatic symptoms in comparison to their caregiver counterparts. Although the reported number of ACEs was the same amongst generations. Also, there was no evidence of correlation between ACEs and mental and physical symptoms in caregivers, while college students did report such correlation. ACEs reported by caregivers showed no correlation to the mental and physical symptoms of their corresponding college student. The findings show that the link between ACEs and health outcomes exhibited generation specific characteristics, with older generations reporting smaller amounts of ACEs and their ACEs not related to mental and physical symptoms. These findings can be framed by the socioemotional selectivity theory (Reed & Carstensen, 2012) postulating that the older generation focuses on positive aspects of life, when compared to their younger counterparts. The findings suggest that although there is continuity of ACEs between generations, the two generations are different in their mental and physical health conditions. Preventative and intervention programs aimed at improving mental and physical functioning may need to consider the generation-specific characteristics to achieve the best effectiveness of the programs.

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The Association of Adverse Childhood Experiences with Anxiety Symptoms Varies with Perceived Level of Stress

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ABSTRACT

Prior research has demonstrated that both adverse childhood experiences (ACEs) and stress predict adult anxiety symptoms. Adverse childhood experiences are traumatizing events that occur by the age 18 and include trauma, neglect, abuse, and family dysfunction. While some research has demonstrated stress playing a role as a mediator in the relation between ACEs and anxiety, more research remains to be done to understand whether stress may serve as a moderator in this relation. Therefore, the purpose of this study was to investigate whether ACEs predicted anxiety symptoms and whether stress moderated this relation. A sample of 624 participants responded to an online survey examining Adverse Childhood Experiences (ACEs), which assessed childhood trauma occurrences prior to one's eighteenth birthday, and current symptoms of depression, anxiety, and stress, which were examined through the Depression Anxiety Stress Scales (DASS). Regression analysis showed that ACEs, stress, and anxiety were mutually correlated. Moderation analysis indicated that stress moderated the relation between ACEs and anxiety. The findings highlight the therapeutic benefits of targeting stress among those who have anxiety associated with ACEs.
Key Words: Adverse childhood experiences, ACEs, stress, anxiety

1. INTRODUCTION

Adverse childhood experiences have been implicated in adult anxiety symptoms in several studies (Anda et al., 2010; Lähdepuro et al., 2019; Sareen et al., 2013). Adverse childhood experiences (ACEs) refer to traumatic experiences that occur within the first 18 years of life, including trauma, abuse, neglect, and family dysfunction (e. g., mental illness, substance abuse, parental separation, and death) (Felitti et al., 1998). Research has also demonstrated that stress plays a role in anxiety symptoms as well (Rideout et al., 2018, Daviu et al., 2019). Stress has both biological and psychological components (Lovibond & Lovibond, 1995). The inability to

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relax and over-reacting in situations are two possible indicators of stress (Lovibond & Lovibond, 1995). Lastly, stress has been investigated as a mediator for the relation between ACEs and anxiety symptoms (Karatekin, 2018). This mediated relationship suggests that stress may also serve as a moderator between ACEs and anxiety; however, a relation has not yet been sufficiently investigated in the literature.

Therefore, this study sought to understand whether stress might moderate the relation between ACEs and adult anxiety symptoms. Based upon previous findings, this study expected to find that ACEs would predict anxiety and that stress would predict anxiety. Additionally, it was expected that stress would moderate the relation between ACEs and anxiety, meaning that stress would change the strength of ACEs and anxiety's relation.

2. METHOD

2.1 Participants and Procedure

A sample of 624 participants (460 females, M_{age} = 27.0, SD_{age} = 14.6) were recruited using the University of Louisiana at Lafayette's Psychology Department SONA participant recruitment system. Participants were provided with the URL to the online survey presented on the Qualtrics platform. Participation was voluntary, and students were awarded credits to partially fulfill research requirements for their Psychology courses.

2.2 Measures

Demographic Information Sheet. The demographics included self-response questions regarding demographic background (e.g., age, gender, race, etc.) and information about their primary caregivers.

Adverse Childhood Experience. The Adverse Childhood Experiences (ACEs; Dong et al., 2003; Felitti et al., 1998) scale is a 10-item self-report questionnaire used to examine an individual's recall of adverse experiences which occurred prior to their eighteenth birthday. These adverse early events pertain to an individual's personal history of emotional abuse, physical abuse, sexual abuse, emotional neglect, physical maltreatment and/or neglect, parental separation/divorce, family substance use, mental illness with the household, and/or parental incarceration. Each of the items are structured as a 'Yes' or 'No' question in regard to the individual's adverse childhood experiences. For instance, an item direct towards a history of physical neglect states "*Did you often or very often feel that (1) no one in your family loved you or thought you were important or special or (2) your family did not look out for each other, feel close to each other, or support each other?*" An exemplar item pertaining to mental illness within the immediate family states "*Was a household member depressed or mentally ill, or did a household member attempt suicide?*" For each item, a 'Yes' response signifies an individual item score of one. The scoring process of ACE is conducted by compositing all the 'Yes' responses from the 10-items; therefore, an individual's ACE score can range from 0 to 10. A score of '0' indicates that the individual experienced no adversities during childhood. According to Dong et al. (2004), an ACE score from 1 to 3 is considered a low occurrence of adverse events. An ACE score of 4 indicates a moderate level of traumatic events, and an ACE score of 5 or more is considered high level of occurrence of adverse events. The Cronbach's alpha for the ACEs scale in the current study was .75.

Depression Anxiety and Stress Scale. The Stress and Anxiety subscales of the Depression

Anxiety and Stress Scale (DASS-21; Lovibond & Lovibond, 1995) were used to assess stress and anxiety symptoms. The DASS-21 is a 21-item scale that measures levels of emotional distress along three dimensions, including depression, anxiety, and stress. The items are rated utilizing a 4-point Likert scale, ranging from 0 (*never*), 1 (*sometimes*), 2 (*often*), and 3 (*almost always*). The DASS-21 contains three 7-item subscales, including the Anxiety, Depression, and Stress subscales. This assessment is defined as a useful tool in determining the severity levels of one's depression, anxiety, and stress as well as how these three variables relate to one another. An exemplar item of the Anxiety subscale is "*I felt I was close to panic",* and an exemplar item for the Stress subscale was *"I found it difficult to relax."* The Cronbach's alphas for the Anxiety and Stress subscales in this study were .81, and .82, respectively.

3. RESULTS

3.1 Correlations

Findings demonstrated that ACEs (M = 1.8, SD = 1.9) were positively correlated with stress (M = 6.8, SD = 4.5), r = .27, p < .001, and anxiety (M = 4.1, SD = 4.5), r = .27, p < .001. Additionally, stress was positively correlated with anxiety, r = .72, p < .001.

3.2 Moderation Analysis

With gender controlled, regression analysis indicated that ACEs significantly predicted anxiety symptoms, b = .11., SE = .03, t = 3.33, p < .001. Additionally, DASS Stress significantly predicted anxiety symptoms, b = .67, SE = .03, t = 22.11, p < .001. Controlling for gender, due to females making up roughly 74% of the participants and the gender differences in the variables, the moderation analysis demonstrated stress having a significant interaction on the relation between ACEs and anxiety symptoms (b = .06, SE = .03, t = 2.33, p = .020), F = 5.41, p = .020, R^2 = .54. Specifically, ACEs and anxiety were positively associated for at medium (b = .11, p = .001) and high (b = .17, p < .001) levels of stress.

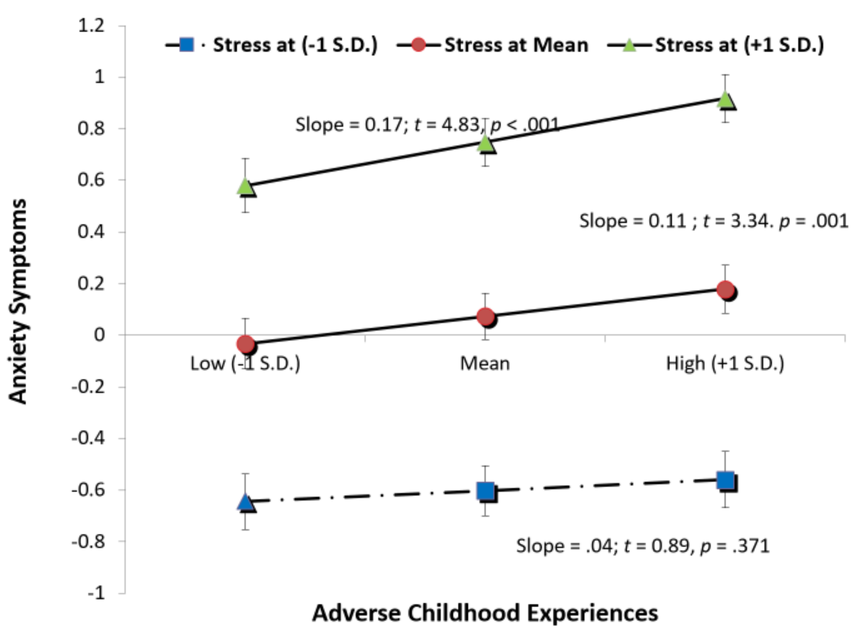

Figure 1. The moderating role of stress in the relation between adverse childhood experiences (ACEs)

and anxiety symptoms. The association of adverse childhood experiences with anxiety symptoms was not significant when the level of stress was low (medium level of stress: $b = .11$, $p = .001$; high level of stress: $b = .17$, $p < .001$). Gender was controlled. All variables were standardized.

4. DISCUSSION

This study examined the relation between ACEs and anxiety symptoms and how stress symptoms moderated this relation. In line with the literature, ACEs and perceived stress, as well as anxiety, were mutually correlated. With gender controlled, moderation analysis on stress revealed a significant interaction effect between ACEs and anxiety. Adverse childhood experiences predicted anxiety symptoms, with higher levels of stress associated with a stronger link between ACEs and anxiety symptoms. This relation may exist as stress led to more anxiety symptoms. Adding to the impact of ACEs on anxiety symptoms (Daviu et al., 2019), stress compounded the anxiety symptoms experienced. The findings were also in line with prior research underscoring stress as a potential moderator through which early childhood trauma was connected to anxiety outcomes (Lähdepuro et al., 2019). According to our data, for individuals who experienced childhood adversity and later developed anxiety symptoms, stress appeared to exacerbate the impact of ACEs on adult anxiety symptoms. To improve anxiety symptoms, screening for exposure to childhood trauma and stress symptoms and implementing interventions for stress symptoms may prove to be essential for ameliorating the harmful effects of childhood adversity on anxiety symptoms.

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Stress Shapes the Associations of Attachment Anxiety with Depression, Anxiety, and Somatic Symptoms

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ABSTRACT
This study aimed to understand how attachment anxiety and stress jointly related to mental and physical symptoms; specifically, depression, anxiety, and somatic symptoms. A sample of 624 participants responded to an online survey examining attachment insecurity and psychological mood and somatic symptoms. Attachment anxiety and stress were positively correlated with depression, anxiety, and physical symptoms. Regression analyses showed a significant effect of interaction between attachment anxiety and stress on depression, anxiety, and somatic symptoms, respectively. These results showed the moderating effect of stress on the associations of attachment anxiety with depression, anxiety, and somatic symptoms; with higher levels of stress associated with increased negative effects of anxious attachment on mental and physical symptoms. The findings provided insights for therapeutic targets of stress among those with anxious attachment in treating adult mental and physical distress symptoms.
Key Words: Attachment anxiety, stress, depression, somatic symptoms

1. INTRODUCTION

Attachment anxiety involves negative views of the *self*, characterized by one's belief that they are not worthy of love and thus is associated with anxiety and fear over rejection by others (Bartholomew & Horowitz, 1991). Mickelson et al. (1997), found that among a national sample, 11% of adults had anxious attachment styles. Therefore, negative consequences associated with anxious attachment need to be examined.

Attachment anxiety has been recognized as a predictor for depression and anxiety (Widom et al., 2018). Children with previous experiences of abuse and neglect were found to be more likely to have anxious attachment styles, which predicted higher levels of anxiety and depression and lower self-esteem (Widom et al., 2018). This connection may identify possible reasons for negative mental health experiences in adults who were subject to neglect and abuse when they were children. Anxious attachment was also linked to increased anxiety symptomology after experiencing stressful events (Jinyao et al., 2012). Somatic symptoms have also been found to be positively correlated with attachment anxiety; specifically, it moderates the relation between adverse childhood experiences and somatic symptoms in adulthood (Lin et al., 2020).

Stress has also been found to negatively affect psychosocial and physical functioning (Lupien et al., 2009). For example, perceived stress has been found to be positively correlated with both depression and anxiety (Wei & Sha, 2003). Stress can also play a moderating role between negative life events and depression; meaning that as stress levels increase, negative life events became more impactful on levels of depression (Kuiper et al. 1986). Additionally, numerous studies have demonstrated that stress has a significant relation with health problems, such as body aches, illness, and migraines (DeLongis et al. 1988; Rawson et al. 1994; Wacogne et al., 2003).

The question arises regarding how attachment anxiety and stress jointly relate to these mental and physical symptoms. Examining whether stress interacts with attachment anxiety may shed light on formulating effective prevention and intervention practices for adult distress symptoms.

2. METHOD

2.1 Participants and Procedure

A sample of 624 participants (460 females, M_{age} = 27.0, SD_{age} = 14.6) responded to an online survey examining attachment insecurity and mood and somatic symptoms. Participants were recruited through the Psychology Department SONA System. Participation was voluntary and granted either SONA credits or extra-course credit. Prior to partaking in the research, participants were told that taking the survey might potentially elicit negative emotional feelings.

2.2 Measures

Experience in Close Relationships. The Experience in Close Relationship Scale–Short Form (ECR-SF; Wei, Russell, Mallinckrodt, & Vogel, 2007) is a 12-item version of the Experience in Close Relationship Scale (Brennan, et al., 1998), which examines internal working models of attachment anxiety and avoidance subscales. This study focused on on the Anxiety subscale, which focuses on fear of abandonment and rejection from others. The subscale has six items, and participants respond to the degree with which they agree with each item on a Likert scale, ranging 1 (*disagree strongly)* to 7 (*agree strongly).* Higher scores on the subscale are associated with increased levels of attachment anxiety. Some exemplar items from this scale are "*I need a lot of reassurance that I am loved by my partner,"* and, *"I find that my partner(s) don't want to get as close as I would like."* The Cronbach's alphas for the ECF-SF Anxiety was .75.

Depression, Anxiety, and Stress. The Depression Anxiety and Stress scale (DASS-21; Lovibond & Lovibond, 1995) is a 21-item scale that measures symptoms of depression, anxiety, and stress through three 7-item subscales. Participants rate how the items describe them on a four-point Likert scale, ranging 0 (*never)* to 3 (*almost always)*. An example from the Anxiety subscale is "*I felt I was close to panic,"* from the Depression subscale, "*I was unable to become enthusiastic about anything,*" and from the Stress subscale, "*I found it difficult to relax.*" The Cronbach's alphas for the Depression, Anxiety, and Stress subscales were .90, .81, and .82, respectively.

Somatic Symptoms. The Somatization subscale of the Symptom Checklist-90—Revised (SCL-90-R, Derogatis, 1994) is a 12-item measure of the effect that somatic symptoms (back pains, headaches, nausea, etc.) have had on psychological distress among participants within the past week. This scale uses a 5-point Likert scale, ranging from 0 (*not at all)* to 4 (*extremely).* Some example items from the scale include, "*Feeling weak in parts of your body,"* and "*Pains in heart or chest."* The Cronbach's alpha for the SCL-90-R somatic subscale for this study was .88.

3. RESULTS

3.1 Descriptive Statistics

In comparison to the original measure's validation scores, the participants reported medium levels of attachment anxiety (M = 21.8, SD = 8.2) and low levels of attachment avoidance (M = 15.0, SD =6.3). On the DASS-21, participants reported normal to mild levels of depressive symptoms (M = 4.8, with SD = 5.2), mild levels of anxiety (M = 4.1, and SD = 4.5), and normal levels of stress (M = 6.8, and SD = 4.6). For the SCL-90, the sample reported relatively low numbers of somatic symptoms they experienced in the past week (M = 0.7, and SD = 0.7).

3.2 Correlations

Attachment anxiety was positively correlated with depression (r = .55, p < 0.001), anxiety (r = .50, p < .001), and physical symptoms (r = .40, p < .001). Stress was also found to be positively correlated with depression (r = .50, p < .001), anxiety (r = .72), and physical symptoms (r = .54, p < .001).

3.3 Regression Analyses

With gender controlled, regression analyses were performed with attachment anxiety and stress as predictors and symptoms of depression, anxiety, and somatic symptoms as criterion variables. Further analyses adding the product term of attachment anxiety and stress were performed to examine the interaction effects of attachment anxiety and stress on mood and somatic symptoms. The results showed significant effects of interaction between attachment anxiety and stress on depression (b = 0.09, p = .004), anxiety (b = 0.15, p < .001), and somatic symptoms (b = 0.09, p = .022). Specifically, as shown in Figure 1, higher levels of attachment anxiety were associated with higher levels of depression at all three levels of stress (low: b = 0.17, p = .001; medium: b = 0.27, p < .001; and high: b = 0.36, p < .001). The same pattern held for both anxiety and somatic symptoms (Figures 2 and 3)—higher levels of attachment anxiety predicted higher levels of anxiety, but only at medium and high levels of stress (medium: b = 0.15, p < .001; and high: b = 0.30, p < .001) and somatic symptoms (low: b = 0.04, p = .502; medium: b = 0.13, p = .007; and high: b = 0.22, p < .001).

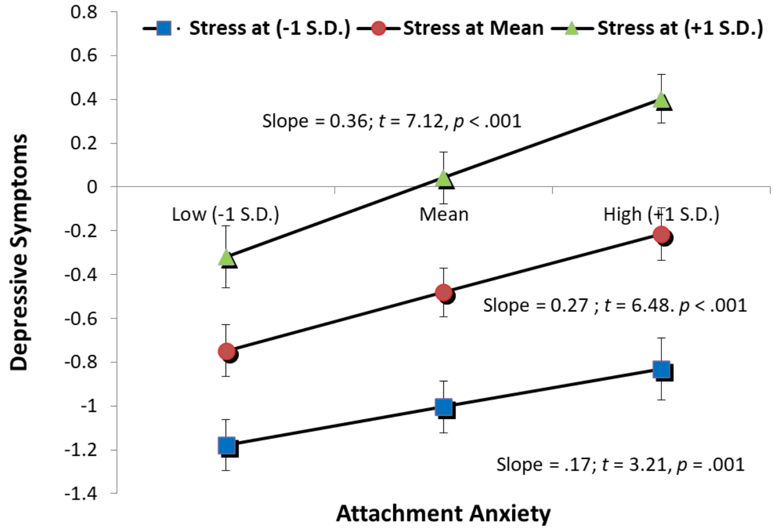

Figure 1. Interaction between attachment anxiety and stress predicting depressive symptoms. All variables were standardized. Gender was controlled.

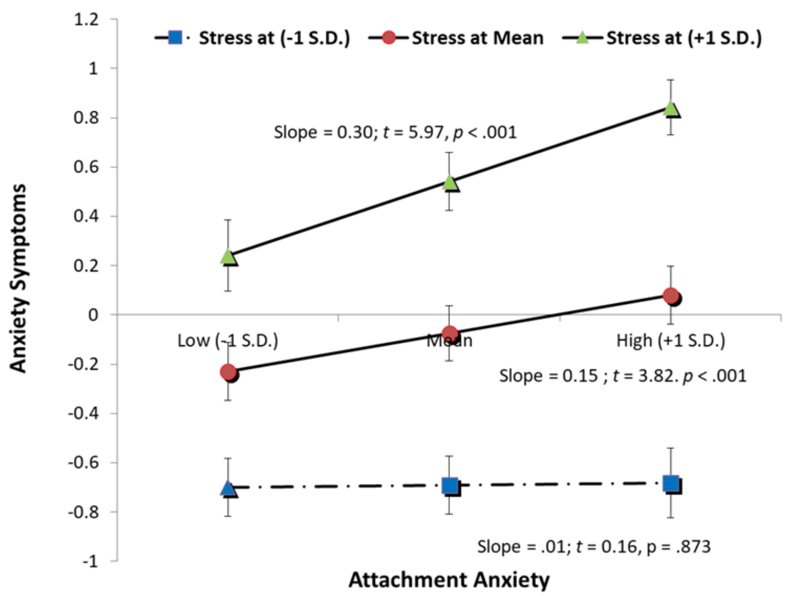

Figure 2. Interaction between attachment anxiety and stress predicting anxiety symptoms. All variables were standardized. Gender was controlled.

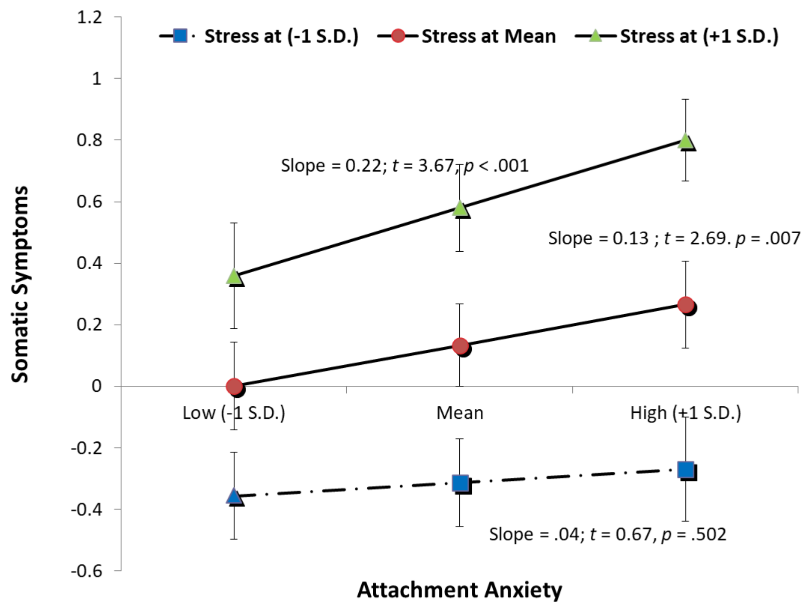

Figure 3. Interaction between attachment anxiety and stress predicting somatic symptoms. All variables were standardized. Gender was controlled.

4. DISCUSSION

The purpose of this study was to examine the relations between attachment anxiety and depression, anxiety, and somatic symptoms. The role of stress in these relations was also investigated.

Attachment anxiety was found to be positively correlated with symptoms of depression, anxiety, and stress, with stress associated with all the mental and physical symptoms. The results also demonstrated a moderating role of stress in each of the associations of attachment anxiety with depression, anxiety, and somatic symptoms, respectively. Specifically, stress exacerbated the negative impacts of attachment anxiety on mental and physical symptoms.

In the past, insecure attachment has been shown to affect both mental and physical health (Berry & Drummond, 2014; Mikulincer & Shaver, 2012). This may be caused by the low levels of self-esteem associated with attachment anxiety, which has been associated with negative consequences in health outcomes (Steiger et al, 2014; Trzesniewski et al., 2006). As such, when levels of attachment anxiety increase, symptoms of depression, stress, and anxiety may also increase. Stress can negatively impact attachment anxiety because the effects of perceived stress can compound with the negative characteristics associated with attachment anxiety (Boyd, 2002). Additional stressors where individuals are faced with diminished relationships (which may occur for those with anxious attachment due to opposition to their fear of being rejected) have been shown to decrease self-esteem, thus resulting in further fear and anxiety over rejection and abandonment (Miller et al., 1989).

These findings provide insights for therapeutic targets of stress among those with attachment anxiety in treating detrimental mental and physical health symptoms. Specifically, among individuals with attachment anxiety, reducing stress has the potential to lower levels of depression, anxiety, and somatic symptoms by reducing the severity of negative mental and physical health outcomes associated with attachment anxiety.

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Bystander Intervention: Greek and Non-Greek Members' Attitudes and Opportunities to Intervene

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ABSTRACT
Objective: The current study aimed to examine the relationships between Greek affiliation and bystander intervention attitudes and opportunities to intervene. We predicted that Greek members (fraternity/sorority members) would have more opportunities to intervene and lower attitudes toward bystander intervention than non-Greek members. **Participants**: Participants include 437 undergraduate students (M_{age} = 19.68; 69% Female) enlisted from a southern university through the university's SONA participant subject pool during the spring and fall semesters of 2020. Of participants, 40 (11.62%) reported being a Greek member while 304 (88.37%) identified as a non-Greek member. **Methods**: Data were collected using The Daily Drinking Questionnaire (Collins et al., 1985) to assess drinking behaviors and a modified version of the Sexual Assault Bystander Questionnaire (Hoxmeier, et al., 2017) to assess the participants' attitudes, subjective norms, perceived behavioral control, self-efficacy, intention, opportunities, and engagement in bystander behavior. **Results**: Results indicated that Greek membership did not influence reported bystander attitudes and opportunities to intervene. **Conclusion**: Due to COVID-19 guidelines and restrictions, the reported opportunities to intervene could have been negatively skewed, and the social distancing guidelines could have potentially caused a disconnect between other sorority/fraternity members, therefore possibly leading to the unobserved differences in attitudes. Despite the null effect reported here, given the current circumstances of COVID-19, researchers should use caution when interpreting the results. Future researchers should continue to examine how greek affiliation may or may not influence bystander perceptions and behavior.
Key Words: Bystander Intervention; Group Differences

1. INTRODUCTION

An estimated 433,000 individuals aged 12 and older are sexually assaulted or raped every year in the United States (RAINN, 2016). On college campuses alone, 23.1% of female and 5.4% of male undergraduate students experience rape or sexual assault (RAINN, 2013). Sexual assault negatively impacts the victim in damaging ways, including psychological, emotional, and physical trauma that can further lead to depression, post-traumatic stress disorder, and other mental illnesses (RAINN, 2020). Because of sexual assault's impact on college students around the United States, many prevention efforts have been developed. One common prevention strategy is bystander intervention. Bystander intervention programs aim to teach bystanders ways to intervene when witnessing sexual assault (Banyard et al., 2007).

Some variables that have been examined in evaluating the effectiveness of bystander intervention programs to reduce sexual violence include rape myth acceptance (RMA), attitudes, social norms, and specific affiliations that college students have (e.g., Greek membership). Previous research has examined the relationship between RMA and Greek membership, athletic membership, and gender (e.g., McMahon, 2010; McMahon et al., 2011).

McMahon (2010) found that sorority/fraternity pledgers were more accepting of rape myths and McMahon et al. (2011) found that sorority/fraternity members had lower attitudes toward bystander intervention. Current studies have also shown that RMA is correlated to bystander intervention; specifically, Jozkowski et al. (2019) found that RMA was negatively associated with willingness to intervene as a bystander. Because McMahon (2010) found that greek membership was associated with greater RMA and Jozkowski et al. (2019) found that RMA was negatively associated with bystander willingness to intervene, this may suggest that greek membership could be associated with bystander intention. When examining bystander opportunities, Hoxmeier al. (2017), found that Greek members reported significantly more opportunities to intervene than non-Greek members. Taken together, these studies show that greek membership could influence bystanders' attitudes toward intervention and opportunities to intervene.

The current study examines the differences between greek and non-greek members' attitudes toward bystander intervention and the reported opportunities to intervene. Following the research discussed above, we predicted that Greek members would have negative attitudes towards bystander intervention in comparison to non-Greek members and that Greek members would have more opportunities to intervene than non-Greek members.

2. METHODS

2.1 Participants & Procedure

Participants included 437 students from a southern university. Students signed up for the study using the university's SONA subject pool and were provided with a link to the survey posted on Qualtrics. A total of 89 participants were removed due to one or more of the following reasons: (1) Incorrectly responding to an attention check item, (2) reporting more engagement in bystander behaviors than opportunities to engage, (3) taking the survey more than once, and/or (4) being under the age of 18. The following analyses were conducted using the remaining 349 participants' data. Participants were predominantly White, Non-Hispanic (69%), female (76%), and in their freshman year of college (61%), with a mean age of 19.68 (*SD* = 3.32).

2.2 Measures

In addition to demographics, participants also completed measures assessing drinking behavior (The Daily Drinking Questionnaire; Collins et al., 1985) and perceptions of bystander intervention. The latter was evaluated using a modified version of the Sexual Assault Bystander Questionnaire (Hoxmeier et al., 2017), which assessed participants' attitudes, subjective norms, perceived behavioral control, self-efficacy, intention, opportunities, and engagement in bystander behavior. For each subscale, one question was given and participants responded to the question across eight scenarios; the same eight scenarios were used for each subscale (e.g., Confront your friend who says he plans to get a girl drunk to have sex").

For the attitudes subscale, participants were asked "if you were to encounter these situations, how helpful or unhelpful do you think performing each action would be?" Response options ranged from 1 (*Totally Unhelpful*) to 7 (*Totally Helpful*). Participants were also given the choice to not respond. This subscale showed high internal reliability (Cronbach's *a* = .91)

For the opportunities subscale, participants were instructed to "indicate how many times you have had the opportunity to take each of these actions in the past three months" Response options included "No Opportunity, 1, 2, ... 9, 10+ times [and] I choose not to respond." The attitudes variable was calculated by using the mean score of the eight attitude items. The opportunities variable was calculated by using the sum of opportunities across all eight opportunity items. This subscale showed high internal reliability (*a* = .93).

2.3 Analyses

First we examine descriptive statistics for greek membership, bystander attitudes, and bystander opportunities. To answer our current research questions, two t-tests were used. The first examined differences between greek and non-greek members' bystander attitudes. The second examined differences between greek and non-greek members' bystander opportunities.

3. RESULTS

3.1 Descriptive Statistics

For descriptive statistics, we examined the proportion of students who identified as greek members and non-greek members. In the current sample, 40 participants (11.62%) identified as a greek member and 304 (88.37%) participants identified as a non-greek member. Four participants chose not respond to the question assessing greek membership and were removed from analyses involving greek membership. For bystander attitudes and opportunities we examined the means and standard deviation of both variables. The current sample has positive bystander attitudes (M = 6.24, SD = 0.91, *Range* 1-7) and few opportunities to intervene (M = 2.51, SD = 9.94, *Range* = 0 - 80).

3.2 Research Questions

We used a t-test to examine if attitudes differed between greek and non-greek members. Figure 1 illustrates the means for the first t-test. The results showed that attitudes were not significantly different, $t(339) = -0.67$, $p = .503$. We used a t-test to examine if bystander opportunities differed between greek and non-greek members. Figure 2 illustrates the means the second t-test. The results showed that opportunities did not significant differ between groups, $t(338) = -0.05$, $p = .962$.

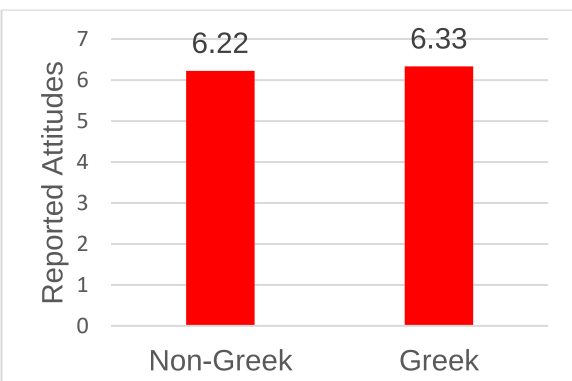

Figure 1. Bystander Attitude by Greek Membership

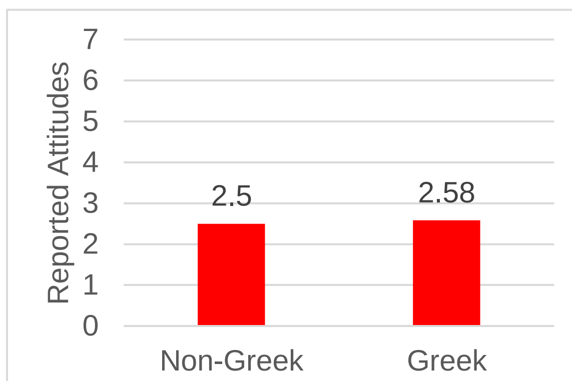

Figure 2. Bystander Opportunities by Greek Membership

4. DISCUSSION

The current study sought to examine differences in bystander attitudes and bystander opportunities between greek and non-greek members. Contrary to previous research examining bystander opportunities (e.g., Hoxmeier et al., 2017), our findings did not show that greek and non-greek members differed from each other. Similarly, bystander attitudes did not differ by greek membership. While we predicted that bystander attitudes between greek and non-greek members would vary due to previous research indicating greek members have higher reported RMA (McMahon, 2010) and lower bystander attitudes (McMahon et al., 2011), the results did not support our prediction.

In the sample from the study by Hoxmeier et al. (2017), only 20% of participants identified as Freshman, while the current sample was composed of 61% Freshman participants. Given that our sample was collected during the spring and fall semesters of 2020 it is likely that participants did not have differences in opportunities to intervene due to the social distancing guidelines implemented with the rise of COVID-19. Similarly, participants identifying as greek members may have also had less opportunities to engage with other fraternity/sorority members which could potentially lead to the unobserved differences in bystander attitudes. Further, out of the 437 participants, only 40 identified as greek members. The combination of most members being freshman and the small proportion of greek members could potentially account for the lack of difference observed here.

In light of the limitations of the current study, the lack of significant differences should be lightly. Future researchers should continue to examine differences in greek and non-greek college students' bystander attitudes and opportunities. As we near the end of the Fall 2020 semester, many social distancing restrictions that were implemented throughout the year are beginning to be lifted, it is possible that greek members may start to experience greater opportunities to intervene as a bystander to prevent potential sexual assaults.

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