**COMPARISON OF SIMPLE MOVING AVERAGE AND ARIMA
TIMESERIES FORECASTING MODELS ON INDEPENDENT HISTORIC
DATA AND EXTRAPOLATING ECHO PROGRAM ATTENDANCE**

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The undersigned, appointed by the Associate Vice Chancellor of the Office of Research and Graduate Studies, have examined the thesis entitled

COMPARISON OF SIMPLE MOVING AVERAGE AND ARIMA TIMESERIES

FORECASTING MODELS ON INDEPENDENT HISTORIC DATA AND

EXTRAPOLATING ECHO PROGRAM ATTENDANCE

presented by **Sara Kasukurthy**,

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LIST OF ABBREVIATIONS

ECHO – Extension of Community Healthcare Outcome - program

AR – Autoregressive

MA – Moving Average

CMA – Centered Moving Average

SMA – Simple (Arithmetic) Moving Average model

ARIMA – Autoregressive Integrated Moving Average model

SARIMA - Seasonal Multiplicative Autoregressive Integrated Moving Average model

VARIMA – Vector Autoregressive Integrated Moving Average model

ES – Exponential Smoothing model

ADF - Augmented Dickey Fuller test

KPSS - Kwiatkowski-Phillips-Schmidt-Shin test

MAE – Mean Absolute Error

MSE – Mean Square Error

MAPE – Mean Absolute Percentage Error

PCP - primary care providers

CME – Continuing Medical Education

UNM – University of New Mexico

RedCap – Research Electronic Data Capture Software

NCRR – National Center for Research Resources

ABSTRACT

Background: The Extension of Community Healthcare Outcome program (ECHO) is an educational and training telemedicine service that provides voluntary case-based learning opportunities for healthcare professionals. Prediction of participant attendance will be useful to improve the sessions with early requirements to maximize the benefits. Usually, the most sophisticated Auto Regressive models are used for forecasting, when the data contains observation with multiple variables and dependencies, Simple Moving Average (SMA) models are used less in such conditions. In this study we want to examine the accuracy and reliability of Moving Average models compared with Auto Regressive models. The objective of this work is to develop an accurate forecasting model for ECHO program attendance by considering non-stationary, independent organizational data.

Methods: The study analyzed 2015-2019 Show Me ECHO attendance data from the Missouri Telehealth Network (MTN). The first step; trained and tested both SMA and ARIMA predictive models without any dependent variables and evaluated both models by measuring error values. The second step; used the best model to forecast ECHO attendance for years 2020 – 2025.

Results: The SMA model was better than the ARIMA model for independent data with lower error values MAE – 38.9, MSE – 2552.15, MAPE – 32.9%, p- value: 3.36E-28, and higher R – square: 87%. Where ARIMA model was with higher error values MAE – 61.8, MSE – 7198.88, MAPE – 37.7%, p- value: 6.25E-22, and lower R – square: 80%.

Conclusion: Simple Moving Average (SMA) is more accurate than Autoregressive Integrated Moving Average (ARIMA) in forecasting future ECHO program attendance. Based on prediction; In 2019, the attendance range was 250-550, where in 2025 it got increased to 530-1170; shows that telehealth attendance will be doubled in the next five years.

Chapter I

INTRODUCTION

Telehealth ECHO programs

ECHO (The Extension of Community Healthcare Outcomes) project is an innovative approach for tele-mentoring of primary care providers (PCPs) practicing in rural, remote, and underserved communities using live-interactive video technology with oral presentations and sharing advanced practice ideas between hub and spoke members to facilitate best practices for patients. [1,2] Project ECHO was a model developed from the idea (future vision) of Dr. Sanjeev Arora, a Hepatologist and Gastroenterologist in University of New Mexico in 2003 to treat (address the growing hepatitis C epidemics) many of Hepatitis C patients throughout the state. [1, 3, 4]

The objective of ECHO model is to provide tele-mentoring and education in best practices, to increase PCPs' capacity to care for patients with complex and chronic conditions, removing some of the access barriers patients might face. [5] The core design of this program includes videoconferencing to merge various interprofessional teams ("hubs") delivering regularly scheduled sessions across multiple health care settings. The subject matter specialists serve as "hub" while "spoke" includes PCPs, nurses, physician assistants and other health care professionals. [5, 6] The ECHO model further encourages "all-teach-all-learn" environment, knowledge sharing beyond one-on-one teaching or discussions. [5]

During each ECHO session the hub team specialists deliver a 10-15 minute didactic, followed by one or more real time patient case presented by participants and used for mentoring and education. [7] Organizations conduct sessions typically weekly or monthly, some ECHOs are year-round, while other follow academic calendars or other individual schedules. One of the main goals of ECHO program is to share latest evidence-based

recommendations and guidelines to reduce variation in care between rural and underserved, and urban areas.

In some isolated areas and rural areas, for providers they have very little opportunities to expand their knowledge with other colleagues and to continue their education with according to the new developments and achievements. Also, they may not contain full-fledged equipment, complex procedures to maintain beneficiary treatment for patients with chronic illnesses. Sometimes it will be a major drawback for uninsured patients where they lack quality (high) care services. If primary care providers in rural areas want to consult with specialties for their patients, they may have limited access to such things, or they may get other difficulties to do so. In these conditions these ECHO sessions are very useful to provide better treatment for patients in less time, with low cost and it is very effective in actions. The committee on ECHO team will share various better ideas among them and will give a best option of treatment through video conferencing. [8]

There are currently 960 ECHO programs from 436 hubs in 45 countries globally.⁵ Of those, 642 programs and 257 hubs are in the United States (as reported on 1/6/2021). [9] As the ECHO model continues to grow and replicate in various clinical and non-clinical applications, it is evident that administrators and other stakeholders will need robust and systematic program evaluation to inform about the effectiveness and efficacy of ECHO.

Evaluation Approach –

ECHO program which adheres to best practices needs proper evaluation process to know the advantages and disadvantages, improvements or to be implemented for better participant experience and satisfaction of involvement. [10] When it comes to research

needed for project ECHO, the priority will be given for evaluation of ongoing project implementations to remodel it as an effective tool for knowledge transfer and for sharing respective experiences of “hub and spoke” members to discuss and improve health care delivery outcomes. Through evaluation approaches we can consider analyzing opportunities like individual provider participation and continuation, involvement of health care organizations, extent of spread/adaptation, positive delivery systems, performance identification and aspects such as organization of specialist teams (hub), primary care provider recruitment, workflow of care delivery support for remodeling/further improvements. [11]

The evaluation of ECHO project includes either process, outcome or economic evaluations. Process evaluation is about program goals and implementations, participants number and characteristics (like whether physician, nurse or other health care providers), project model and activities, accomplishments and outcomes. [12,13] Outcome evaluation will focus on assessing the outcome results such as improvements in knowledge and self-efficacy, changes in treatment practices, professional satisfaction and confidence, patient outcomes, costs and care utilization variations/changes. [14] Economic evaluation includes expenses for implementations, program deliveries for the benefits obtained from sessions, ROI (return on investment) calculations, cost effective, efficient and benefit analyses. [15] This evaluation can be done with different program performance measuring models such as, Kirkpatrick evaluation and Moore evaluation which guides perfectly in measuring specific program efficiency and effectiveness.

MTN Show-Me ECHO –

Missouri telehealth network (MTN) started Show Me ECHO program with pain management sessions in November 2014 (move knowledge not patients). Since then, it is growing in a fascinating way which has 108 counties across Missouri state and 790 organizations involvement/participation in overall 35 ECHO topics till July 2020. Also, MTN Show Me ECHO program is one of 13 global super hubs for training other organizations to start/create ECHOs.

Figure 1: MTN Show Me-ECHO timeline

Figure 2: Available Data in MTN Show Me-ECHO

For data collection process Missouri Telehealth Network usually follows through RedCap, which is safe and secure, for registrations (registers interest in a topic) & pre-survey, roll call (before every individual session), case presentation (participant) and recommendation (hub team) forms, semi-annual self-efficacy surveys (and any additional question), opt-out (exit survey). Data storage through MarketVolt - email marketing software for General communications, weekly session invitations (with links) and iECHO which is required by Project ECHO for session attendance information and for Being phased out (both by Project ECHO and MTN). Box will be using for document storage with excel, SAS, SPSS files, just obtained for analysis.

Figure 3: Current Data flow & proposed for Daily Operations in MTN - ECHO

Figure 4: Current Data flow & Proposed for Evaluation in MTN - ECHO

Time series analysis

Time series analysis involves developing models that best capture or describe an observed time series to understand the underlying causes. The four components that time series analysis will decompose the data into an estimation are secular trend, seasonal variations, cyclical fluctuations, and irregular variations, each expressing a particular aspect of the movement of the values of the time series. [16]

Figure 5: Time Series Components

Some important data characteristics involved in time series analysis are data stationarity, seasonality, and autocorrelation. Stationarity – when the statistical properties of data do not change according to time, when the data has constant mean, variance, and covariance with independent of time, that means the data is stationary. Mostly time series models are used on non-stationary data by converting that to stationary. Usually, regression models are effective on data which has dependent variables and moving average models on data with independent variables. Seasonality – the characteristic of periodic fluctuations and

changes in data points trend according to seasons is known as seasonality in data. Autocorrelation - means the similarity between observations as a function of time lag between them. [17]

Time series forecasting

Forecasting involves taking models fit on historical data and using them to predict future observations. The three general types of forecasting techniques used for organizational data for predictions are qualitative techniques, time series analysis and projection and causal models. Time series analysis consists of moving average, exponential smoothing, trend projections and Box-Jenkins technique, causal model contains mainly regression models. The five common algorithms are Linear Regression (LR), Simple Moving Average (SMA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ES). [18]

Health care organizations need forecasting method implementations to manage decision making for health services and the four major common forecasting methods are 12-month moving average, trendline, percent adjustments and seasonalized forecast, which are dependent on recent historical data demand of organization. [19]

Figure 6: Time Series Forecasting methods

Objectives

1. Implementation and comparison of both Simple Moving Average and ARIMA time series models on organizational independent data to find out which time series model is well fitted for predicting future values?
2. Forecasting future ECHO participants attendance using more efficient time series model for future implementations and improvements and to support thesis hypothesis “Telemedicine ECHO project awareness/progression and health professional's participation will increase in the future”.

Chapter II

SYSTEMATIC LITERATURE REVIEW

An electronic literature search was performed in MEDLINE (OVID) with inclusion criteria of certain keywords and articles from 1946 to May 04, 2021.

Search Keywords: Time series analysis, time series forecasting, prediction, moving average, ARIMA, autoregression, evaluation of time series forecasting.

Table 1: Medline (Ovid) search strategy/terms

S. No	Search Terms	Results
1	time series analysis.mp.	5724
2	forecasting.mp. or Forecasting/	91747
3	moving average.mp.	2507
4	ARIMA.mp.	904
5	autoregressive integrated moving average.mp.	700
6	evaluation of time series.mp.	17
7	3 and 4	4501
8	3 and 4 and 5	408
9	2 and 6	3
10	2 and 3 and 4	177
11	limit 10 to (English language and full text)	13

Considered 177 articles from “forecasting and moving average and ARIMA” keyword combination search and three articles about evaluation methods were also considered for initial screening. After removal of 87 duplicates, 93 were screened for availability of full text and selected 16 articles under eligibility and 3 free web search articles were included to the list. Total 19 articles were selected, many of them stating the same point for conclusion that ARIMA model is highly considerable among regression models, here selected 7 articles, one each of different statements for decision making of procedures.

Figure 7: PRISMA 2009 Flow Diagram

- 1. Zoran Ivanovski, Ace Milenkovski, and Zoran Narasanov. 2018. Time Series Forecasting Using a Moving Average Model for Extrapolation of Number of Tourist. UTMS Journal of Economics 9 (2): 121–132.**

The study consists of quarterly data for total number of guests for the five years period from 2012– 2016 and extrapolated number of guests quarterly for 2017. The authors in this study stated that moving average model is the most suitable forecasting approach when the observations mainly depend on error terms, means not on past values or on any other dependent variables and which follows a white noise process (purely random in nature). They observed relatively small difference between actual and forecasted values for the first two quarters of 2017 (8% and 1%), so concluded that the moving average time series model provides accurate forecasting values for independent data and this is the starting point for my thesis about proving Moving Average model is the best model compared to Autoregressive models. [20]

- 2. Aryee, G., Kwarteng, E., Essuman, R., Nkansa Agyei, A., Kudzawu, S., Djagbletey, R., Owusu Darkwa, E., Forson, A. (2018). Estimating the incidence of tuberculosis cases reported at a tertiary hospital in Ghana: a time series model approach. BMC Public Health, 18, 1292.**

The main aim of considering this study was to assess the effectiveness of ARIMA time series model to estimate the incidence of TB cases at teaching hospital. They conducted auto regressive integrated moving average (ARIMA) model on monthly cases to see the trends and seasonal changes in number of patients presenting with TB worldwide from 2008 to 2017. They finalized ARIMA (1,0,1) as best model which produced 0.971 AR coefficient and -0.826 MA coefficient. Further they forecasted monthly values for 2018

with the best model they obtained (ARIMA (1,0,1)) and observed the different range between 50-55. [21]

- 3. Briet, O. J., Vounatsou, P., Gunawardena, D. M., Galappaththy, G. N., Amerasinghe, P. H. (2008). Models for short term malaria prediction in Sri Lanka. Malaria Journal, 7, 76.**

The main aim of the study was to develop a forecasting system which could be used to assist in the efficient allocation of resources for malaria control, by considering a long time series of monitored/diagnosed malaria cases for the study of forecasting models. They conducted and compared Exponentially weighted moving average models, autoregressive integrated moving average (ARIMA) models with seasonal components, and seasonal multiplicative autoregressive integrated moving average (SARIMA) models on monthly time series cases to check model ability in predicting numbers for one to four months ahead. They found out that the best model varied distinctly throughout the districts and forecasting horizons, but most often SARIMA class models showed least mean absolute relative prediction errors. [22]

- 4. Loha, E., Lindtjorn, B. (2010). Model variations in predicting incidence of plasmodium falciparum malaria using 1998-2007 morbidity and meteorological data from south Ethiopia. Malaria Journal, 9, 166.**

In this study, researchers implemented 35 models on data consists P. falciparum malaria incidence for the period of 1998-2007 and meteorological variables such as monthly rainfall (all locations), temperature (17 locations), and relative humidity (three locations) and considered R squared or stationary R squared values to measure the model fitness.

Time series modelling was carried out using Transfer Function (TF) models and univariate auto-regressive integrated moving average (ARIMA) when there was no significant predictor meteorological variable. They observed R squared values for the models ranged from 16% to 97%, except for one model which had a negative value and models with seasonal ARIMA orders were found to perform better, so considered ARIMA model as the second forecasting model to compare with Moving Average model. [23]

5. **Mai, Q., Aboagye-Sarfo, P., Sanfilippo, F. M., Preen, D. B., Fatovich, D. M. (2015). Predicting the number of emergency department presentations in western Australia: a population-based time series analysis. *Emergency Medicine Australasia*, 27, 16-21.**

The main aim of the study is predicting number of emergency department presentations in the next five years with the data consists of dependent variables like place of treatment, age, triage and disposition. They considered monthly data from years 2006/07 – 2012/13 financial years and used univariate autoregressive integrated moving average (ARIMA) and multivariate vector-ARIMA techniques. The findings are ED presentations in WA were predicted to increase from 990 342 in 2012/13 to 1 250 991 (95% CI: 982 265–1 519 718) in 2017/18, an increase of 260 649 (or 26.3%) and majority of increase they found in metropolitan WA (84.2%). Concluded that time series analysis, particularly VARIMA is most reliable tool for predicting demand by categories. [24]

6. **N'gattia, A. K., Coulibaly, D., Nzussouo, N. T., Kadjo, H. A., Cherif, D., Traore, Y., Kouakou, B. K., Kouassi, P. D., Ekra, K. D., Dagnan, N. S., Williams, T., Tiembre, I. (2016). Effects of climatological parameters**

in modeling and forecasting seasonal influenza transmission in Abidjan, cote d'ivoire. BMC Public Health, 16, 972.

The main aim of the current study is to identify and model the effects of climatological parameters on seasonal influenza activity and forecasting values for ahead of time. They conducted multivariant and univariant autoregressive integrated moving average model (ARIMA) to create models on data from 2007-2010 and to assess the predictive values by best fitted model on data from 2011 – 2012 and compared both performances based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Finally concluded that multivariant ARIMA (2,0,0) model as best fitted model with 95% confidence interval on predicted values. [25]

7. Tapak, L., Hamidi, O., Fathian, M., Karami, M. (2019). Comparative evaluation of time series models for predicting influenza outbreaks: application of influenza-like illness data from sentinel sites of healthcare centers in iran. BMC Research Notes, 12, 353.

In this study researchers investigated the accuracy of support vector machine, artificial neural-network, and random-forest time series models in influenza like illness (ILI) modeling, outbreaks detection and evaluated through Root Mean Square Errors (RMSE), Mean Absolute Errors (MAE), and Intra-Class Correlation Coefficient (ICC) statistics. With RMSE=22.78, MAE=14.99 and ICC=0.88 for random forest time series on test set. From this study we considered using error measures is an efficient way to evaluate the models. [26]

Chapter III

METHODOLOGY

Study Design

The data source we selected was Missouri Telehealth Network (MTN) Show Me-ECHO data repository from iECHO and RedCap. Show Me-ECHO data comprise of 39797 observations (attendance) from 09/20/2014 (inception) – 10/20/2020 (data collection end date), includes 35 types of ECHO programs data. As of inclusion criteria, we considered data from 01/01/2015 – 12/31/2019 for time series analysis and excluded data from Oct 2014 – Dec 2014, (due to unavailability of data for the whole 2014) and data from Jan 2020 - Dec 2020, (because of COVID-19 pandemic there is more involvement of participants in topics related to pandemic (COVID-19, COVID-19 Kids, Moms & Babies COVID) due to remote working, interest in current situation and also due to decrease in direct patient care involvement) which is inconsistent/inappropriate to compare with other years since we are predicting monthly attendance. We selected most widely used models ARIMA (Autoregressive Integrated Moving Average) and SMA (Simple Moving Average) from each Autoregressive and Moving Average forecasting algorithms for comparison of prediction values. As of evaluation of models, we followed scale-dependent measures like Mean Square Error (MSE), Mean Absolute Error (MAE) and measures based on percentage errors such as Mean Absolute Percentage Error (MAPE) which are widely used methods along with R-Square values and p-Value of both models.

Programming – Python (ADF test): Evaluation of initial data to test data stationarity, Excel: Both Simple Moving Average and ARIMA models on dataset for forecasting, Evaluating model fitness on data.

Data Resource Instruments/Tools

RedCap: RedCap is a metadata driven electronic data capture web-based software which can be used for designing and processing of surveys, storing and mining of confidential multi-dimensional data. It is an exceptional secured clinical and translational research database workflow management system supported by NCCR grants and NIH [27, 28]. It was developed in 2004 [29] by an informatics team at Vanderbilt University to address using electronic data bases and to support multidisciplinary independent research environments which lacks effective IT integration in protocols. [30] Some features include Easy survey design (wide choice of question types, quality checks, limited layout capabilities), versatile survey taking options (open surveys with links, personal, schedules invitations, offline staff editing), few native data analysis capabilities (data export to excel, R, SAS, SPSS files).

iECHO: It is a web based tool started in 2010 by University of New Mexico [UNM] to manage and inspect tele ECHO clinics about clinic performance by collecting data and serves as a resource provider for partners (collaborative organizations). It was designed to track and report tele ECHO program components, for iECHO informational storage includes program administrative data, attendance records for participants and facilitators, case presentation metrics, didactic presentations, program documents, and awarded CME/CEU/CE credits. The software is not meant to store any health information of individuals. [31]

Procedure

Figure 8: Data Observations & Analysis Study Process

Chapter IV

RESULTS

1. Descriptive Analysis of Data

We analyzed the raw data to get familiar with observations for further analysis and obtained various kinds of information such as number of ECHO sessions and topics that the organization is conducting, type of participants, participating organizations, along with that we observed elevations in ECHO programs and participants from inception in 2014 to current 2020.

Table 2: Show-Me ECHO Disease Variables

S.No	Topic	Start Date	Last Date	Still in Progress	No. Sessions	Total Observations	Total count (Unique Individuals)		
							No. Attendees	No. Facilitators	No. Counties involved
1	Asthma	9/8/2015	10/13/2020	Yes	157	4910	825	27	61
2	ATTC	9/26/2016	1/10/2017	No	7	48	10	10	3
3	Autism	2/4/2015	10/19/2020	Yes	342	5440	751	64	80
4	Certified Peer Specialist	2/5/2020	10/7/2020	Yes	17	468	111	6	34
5	Child Psych	1/10/2017	10/9/2020	Yes	45	1141	295	10	47
6	CHW	1/10/2017	10/6/2020	Yes	52	2642	378	13	63
7	COVID 19	3/23/2020	10/12/2020	Yes	28	5890	1050	12	97
8	COVID 19&Kids	9/17/2020	10/15/2020	Yes	5	646	311	10	64
9	Crown	2/28/2019	12/12/2019	No	17	215	48	10	18
10	Dermatology	11/20/2015	10/16/2020	Yes	110	2133	254	14	38
11	Developmental Disabilities	8/8/2019	10/8/2020	Yes	23	401	156	8	39
12	Endocrinology	8/20/2015	12/13/2016	No	42	526	115	7	18
13	Foot Preservation	9/2/2020	10/7/2020	Yes	2	28	11	9	9
14	Genetics	2/14/2019	5/23/2019	No	2	5	5	0	4
15	Head Start	1/15/2020	9/16/2020	Yes	6	129	54	9	17
16	Healthcare Ethics	1/10/2017	6/13/2019	No	18	311	89	9	19
17	HIV	11/8/2018	10/8/2020	Yes	11	238	78	10	9
18	Hope	2/5/2019	12/17/2019	No	19	257	49	13	11
19	Hypertension	10/28/2019	10/12/2020	Yes	11	273	82	10	30
20	Kidney Disease	10/3/2019	8/15/2019	Yes	26	605	122	13	38
21	Missouri Moms & Babies	6/24/2020	10/14/2020	Yes	8	298	110	13	28

22	MTSS	4/17/2018	2/27/2020	No	18	315	128	9	21
23	NAS	2/7/2019	10/3/2019	No	17	216	61	9	17
24	Nurse Education	1/9/2019	4/22/2020	No	21	1550	541	3	103
25	Oral Health	2/13/2019	10/14/2020	Yes	20	373	109	11	31
26	ODD	1/10/2017	10/9/2020	Yes	52	1178	366	12	51
27	Pain Management	11/16/2014	10/8/2020	Yes	92	2344	433	17	44
28	Pediatric Sleep	8/10/2020	10/12/2020	Yes	7	108	33	6	15
29	PrEP	8/7/2019	9/18/2019	No	4	5	1	4	4
30	Rural Veterans	9/5/2018	7/23/2019	No	19	239	48	7	20
31	SEMO Diabetes	9/3/2019	5/19/2020	No	17	395	88	9	28
32	Telemedicine	4/14/2020	10/13/2020	Yes	21	503	152	3	40
33	Trauma Informed Schools	11/19/2019	9/8/2020	Yes	12	341	171	9	43
34	Urban Dermatology	2/12/2020	5/13/2020	No	4	35	19	2	6
35	Viral Hepatitis & Fatty Liver	1/20/2016	10/16/2020	Yes	67	980	147	17	33

MTN Show me ECHO program has 35 program topics started on differed dates from Oct' 2014 – Dec' 2020. Table 2: shows individual details about specific program such as number of sessions conducted, number of attendees, facilitators and counties involved.

2. Comparison study Results –

Tested both SMA and ARIMA on actual data and calculated prediction values for actual values (2015 – 2019) and to select appropriate time series analysis type for forecasting, compared R-square value and p-value through basic regression test and error scale measures like Mean Square Error (MSE), Mean Absolute Error (MAE) and measures based on percentage errors such as Mean Absolute Percentage Error (MAPE) were used due to their high efficiency.

Figure 9: Comparison of SMA and ARIMA forecasting models (2015 – 2019)

Table 3: Comparison of SMA and ARIMA forecasting models (2015 – 2019)

Error tests	SMA Values	ARIMA Values	Reference Values
MAE/MAD	38.90	61.82	0 to ∞ (Lower values are better)
MSE	2552.15	7198.88	-10,000 - +10,000
MAPE	32.9%	37.7%	< 10% is Excellent, < 20% is Very Good
R-square value	0.878	0.805	
p-value	3.36E-28	6.25E-22	

So, we selected SMA model with lower error values, MAE – 38.9, MSE – 2552.15, MAPE – 32.9%, p- value: 3.36E-28, and higher R – square: 87% for forecasting, Where ARIMA model was with higher error values MAE – 61.8, MSE – 7198.88, MAPE – 37.7%, p-value: 6.25E-22, and lower R – square: 80%.

3. SMA Time Series Forecasting Values –

Predicted attendance from January 2020 – December 2025 using Simple Moving Average which was proved as a better prediction model for the current dataset.

Table 4: Future Predicted Attendance (Simple Moving Average Forecasting) (2020-2025)

Month	2020	2021	2022	2023	2024	2025
Jan	514	621	729	837	945	1052
Feb	538	649	760	871	981	1092
Mar	497	597	698	799	899	1000
Apr	484	580	676	773	869	965
May	470	562	654	746	839	931
Jun	440	525	610	694	779	864
Jul	269	320	371	422	473	524
Aug	308	366	423	481	538	596
Sep	608	720	832	944	1056	1168
Oct	606	716	826	936	1045	1155
Nov	511	603	694	785	876	968
Dec	383	450	518	585	652	720

Figure 10: Attendance both Actual Past (2015-2019) and Future Predicted (2020-2025)

The findings from forecasting step indicates that in 2019, the attendance range was 250-550, where in 2025 it is increased to 530-1170; this says that telehealth attendance will be doubled in the next five years.

Chapter V

CONCLUSION

The main purpose of this study is to prove that telemedicine ECHO project progression and health professional's participation will observe an uptrend in the future. To support this statement, during the early stages of the study we were interested in predicting the future values and see the trend in participation of training programs.

We identified that SMA model is the best forecasting technique compared with ARIMA model for datasets with independent variables and non-stationary trends. There will be an increase in care providers participation in telehealth related programs includes educational, training programs where the development and utilization of telemedicine services is important, as these services allow health care professionals to continue in providing high-quality healthcare.

As further and prospective use of current study statements, this type of forecasting analysis helps to identify irregularities, systematic variations in data series including seasonality, data trends, growth rates and cyclic patterns. [32] By considering limited independent quantitative data in preliminary analysis this method is useful to predict future census in hospital units like in emergency departments to correspond with proper utilization measures by anticipating cases ahead of time [25, 33], in quality improvement programs, like predicting intensive care unit readmissions and needed facility arrangements, like improving appointment scheduling. [36] Also useful in analyzing Disease outbreaks and infectious disease surveillance by using existed data in predicting disease patterns helps in minimizing disease impact with early preventive measure follow ups, population health messaging and escalating clinicians' awareness for timely treatment and diagnosis. [26, 33, 34, 35]

While the researchers still agree to the findings and conclusions, there are some limitations in the study like – 1.) data does not have any dependent variables, 2.) data is not stable and sample size is very small with only 60 observations. The availability of long time series data for the study of different models is very important in developing efficient forecasting system. [22], and limitation 3.) data contains some ECHOs which are ended before Dec 2020.

REFERENCES

1. Project ECHO. (n.d.). Retrieved May 5, 2021, from <https://hsc.unm.edu/echo/>
2. Komaromy, M., Ceballos, V., Zurawski, A., Bodenheimer, T., Thom, D. H., & Arora, S. (2018). Extension for Community Healthcare Outcomes (ECHO): A new model for community health worker training and support. *Journal of Public Health Policy*, 39(2), 203–216. <https://doi.org/10.1057/s41271-017-0114-8>
3. Arora, S., Thornton, K., Murata, G., Deming, P., Kalishman, S., Dion, D., Parish, B., Burke, T., Pak, W., Dunkelberg, J., Kistin, M., Brown, J., Jenkuskys, S., Komaromy, M., & Qualls, C. (2011). Outcomes of treatment for hepatitis C virus infection by primary care providers. *The New England Journal of Medicine*, 364(23), 2199–2207. <https://doi.org/10.1056/NEJMoa1009370>
4. Katzman, J. G., Galloway, K., Olivas, C., McCoy-Stafford, K., Duhigg, D., Comerchi, G., Kalishman, S., Buckenmaier, C. C., McGhee, L., Joltes, K., Bradford, A., Shelley, B., Hernandez, J., & Arora, S. (2016). Expanding Health Care Access Through Education: Dissemination and Implementation of the ECHO Model. *Military Medicine*, 181(3), 227–235. <https://doi.org/10.7205/MILMED-D-15-00044>
5. Carlin, L., Zhao, J., Dubin, R., Taenzer, P., Sidrak, H., & Furlan, A. (2018). Project ECHO Telementoring Intervention for Managing Chronic Pain in Primary Care: Insights from a Qualitative Study. *Pain Medicine (Malden, Mass.)*, 19(6), 1140–1146. <https://doi.org/10.1093/pm/pnx233>
6. Frank, J. W., Carey, E. P., Fagan, K. M., Aron, D. C., Todd-Stenberg, J., Moore, B. A., Kerns, R. D., Au, D. H., Ho, P. M., & Kirsh, S. R. (2015). Evaluation of a telementoring intervention for pain management in the Veterans Health

- Administration. *Pain Medicine* (Malden, Mass.), 16(6), 1090–1100.
<https://doi.org/10.1111/pme.12715>
7. De Witt Jansen, B., Brazil, K., Passmore, P., Buchanan, H., Maxwell, D., McIlfatrick, S. J., Morgan, S. M., Watson, M., & Parsons, C. (2018). Evaluation of the impact of telementoring using ECHO© technology on healthcare professionals' knowledge and self-efficacy in assessing and managing pain for people with advanced dementia nearing the end of life. *BMC Health Services Research*, 18(1), 228. <https://doi.org/10.1186/s12913-018-3032-y>
 8. Arora, S., Kalishman, S., Dion, D., Som, D., Thornton, K., Bankhurst, A., Boyle, J., Harkins, M., Moseley, K., Murata, G., Komaramy, M., Katzman, J., Colleran, K., Deming, P., & Yutzy, S. (2011). Partnering urban academic medical centers and rural primary care clinicians to provide complex chronic disease care. *Health Affairs (Project Hope)*, 30(6), 1176–1184.
<https://doi.org/10.1377/hlthaff.2011.0278>
 9. Hubs & Programs. (n.d.). Retrieved December 18, 2020, from <https://hsc.unm.edu/echo/data-marketplace/interactive-dashboards/>
 10. Lewiecki, E. M., & Rochelle, R. (2019). Project ECHO: Telehealth to Expand Capacity to Deliver Best Practice Medical Care. *Rheumatic Diseases Clinics of North America*, 45(2), 303–314. <https://doi.org/10.1016/j.rdc.2019.01.003>
 11. Dearing, J. W. (n.d.). Project ECHO: Review and Research Agenda. 47. <http://www.diffusionassociates.com/wp-content/uploads/2019/09/echo.pdf>
 12. Saunders, R. P., Evans, M. H., & Joshi, P. (2005). Developing a process-evaluation plan for assessing health promotion program implementation: A how-to guide.

Health Promotion Practice, 6(2), 134–147.
<https://doi.org/10.1177/1524839904273387>

13. White, W. L. (2004). Process Evaluation for Public Health Interventions and Research: Process Evaluation for Public Health Interventions and Research; Allan Steckler, Laura Linnan (Eds.); Jossey-Bass, San Francisco, CA, 2002, 400 pages.
Evaluation and Program Planning, 27(1), 118–119.
<https://doi.org/10.1016/j.evalprogplan.2003.09.006>
14. Friedman, M. (n.d.). Results-Based Accountability Producing Measurable Improvements for Customers and Communities. 8.
<https://www.oecd.org/site/progresskorea/44120813.pdf>
15. Drummond MF, O'Brien B, Stoddart GL, Torrance GW. (1997). Methods for the Economic Evaluation of Health Care Programs, 2nd ed. Oxford Medical Publications, Oxford University Press, New York.
16. Time Series. (2008). In the Concise Encyclopedia of Statistics (pp. 536–539). Springer. https://doi.org/10.1007/978-0-387-32833-1_401
17. Peixeiro, M. (2021, April 18). The Complete Guide to Time Series Analysis and Forecasting. Medium. <https://towardsdatascience.com/the-complete-guide-to-time-series-analysis-and-forecasting-70d476bfe775>
18. How to Choose the Right Forecasting Technique. (n.d.). Retrieved May 5, 2021, from <https://hbr.org/1971/07/how-to-choose-the-right-forecasting-technique>
19. Côté, M. J., & Tucker, S. L. (2001). Four methodologies to improve healthcare demand forecasting. Healthcare Financial Management: Journal of the Healthcare Financial Management Association, 55(5), 54–58.

20. Zoran Ivanovski, Ace Milenkovski, and Zoran Narasanov. 2018. Time Series Forecasting Using a Moving Average Model for Extrapolation of Number of Tourist. *UTMS Journal of Economics* 9 (2): 121–132. <https://www.researchgate.net/publication/329714218>
21. Aryee, G., Kwarteng, E., Essuman, R., Nkansa Agyei, A., Kudzawu, S., Djagbletey, R., Owusu Darkwa, E., Forson, A. (2018). Estimating the incidence of tuberculosis cases reported at a tertiary hospital in Ghana: a time series model approach. *BMC Public Health*, 18, 1292. <https://doi.org/10.1186/s12889-018-6221-z>
22. Briet, O. J., Vounatsou, P., Gunawardena, D. M., Galappaththy, G. N., Amerasinghe, P. H. (2008). Models for short term malaria prediction in Sri Lanka. *Malaria Journal*, 7, 76. <http://www.malariajournal.com/content/7/1/76>
23. Loha, E., Lindtjorn, B. (2010). Model variations in predicting incidence of plasmodium falciparum malaria using 1998-2007 morbidity and meteorological data from south Ethiopia. *Malaria Journal*, 9, 166. <http://www.malariajournal.com/content/9/1/166>
24. Mai, Q., Aboagye-Sarfo, P., Sanfilippo, F. M., Preen, D. B., Fatovich, D. M. (2015). Predicting the number of emergency department presentations in western Australia: a population-based time series analysis. *Emergency Medicine Australasia*, 27, 16-21. <https://pubmed.ncbi.nlm.nih.gov/25583296/>
25. N'gattia, A. K., Coulibaly, D., Nzussouo, N. T., Kadjo, H. A., Cherif, D., Traore, Y., Kouakou, B. K., Kouassi, P. D., Ekra, K. D., Dagnan, N. S., Williams, T., Tiembre, I. (2016). Effects of climatological parameters in modeling and

- forecasting seasonal influenza transmission in Abidjan, cote d'ivoire. BMC Public Health, 16, 972. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5022141/>
26. Tapak, L., Hamidi, O., Fathian, M., Karami, M. (2019). Comparative evaluation of time series models for predicting influenza outbreaks: application of influenza-like illness data from sentinel sites of healthcare centers in iran. BMC Research Notes, 12, 353. <https://doi.org/10.1186/s13104-019-4393-y>
 27. REDCap. (2021). In Wikipedia. <https://en.wikipedia.org/w/index.php?title=REDCap&oldid=1023904087>
 28. Software – REDCap. (n.d.). Retrieved May 21, 2021, from <https://projectredcap.org/software/>
 29. Harris, P. A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., & Conde, J. G. (2009). Research Electronic Data Capture (REDCap)—A metadata-driven methodology and workflow process for providing translational research informatics support. Journal of Biomedical Informatics, 42(2), 377–381. <https://doi.org/10.1016/j.jbi.2008.08.010>
 30. Zerhouni, E. A. (2003). A New Vision for the National Institutes of Health. Journal of Biomedicine and Biotechnology, 2003(3), 159–160. <https://doi.org/10.1155/S1110724303306023>
 31. IECHO. (n.d.). Retrieved May 21, 2021, from <https://iecho.unm.edu/>
 32. How to Choose the Right Forecasting Technique. (n.d.). Retrieved May 21, 2021, from <https://hbr.org/1971/07/how-to-choose-the-right-forecasting-technique>
 33. Capan, M., Hoover, S., Jackson, E. V., Paul, D., & Locke, R. (2016). Time Series Analysis for Forecasting Hospital Census: Application to the Neonatal Intensive

Care Unit. *Applied Clinical Informatics*, 7(2), 275–289.
<https://doi.org/10.4338/ACI-2015-09-RA-0127>

34. Reis, B. Y., & Mandl, K. D. (2003). Time series modeling for syndromic surveillance. *BMC Medical Informatics and Decision Making*, 3, 2.
<https://doi.org/10.1186/1472-6947-3-2>
35. Brillman, J. C., Burr, T., Forslund, D., Joyce, E., Picard, R., & Umland, E. (2005). Modeling emergency department visit patterns for infectious disease complaints: Results and application to disease surveillance. *BMC Medical Informatics and Decision Making*, 5, 4. <https://doi.org/10.1186/1472-6947-5-4>
36. Platforms of Intelligence for healthcare providers and payers: The path to personalization and efficient operations. (2020, September 17). ITC Infotech.
<https://www.itcinfotech.com/blog/platforms-of-intelligence-for-healthcare-providers-and-payers/>

APPENDIX

MTN ECHO Data specific details -

ECHO Participant Type

	2014	2015	2016	2017	2018	2019	2020
Physician (MD, DO)	3	68	138	171	180	241	370
Clinical Pharmacist (PharmD)	0	3	6	13	18	18	33
Physician Assistant (PA, MHS)	0	3	5	7	8	16	9
Advanced Practice Nurse (NP, CRNA, CNM, CNS, etc)	1	12	31	31	35	71	146
Registered Nurse (RN, BSN)	4	29	46	101	111	549	742
Licensed Practical Nurse (LPN)	3	9	25	18	16	110	87
Family Nurse Practitioner (FNP)	1	8	13	9	12	21	41
Medical Assistant (MA, CMA)	1	4	14	19	25	34	39
Certified Nursing Assistant (CAN)	0	0	0	0	0	0	0
Registered Pharmacist (RPh)	0	3	2	1	1	2	0
Registered Dietitian (RD)	1	1	5	5	0	4	8
Community Health Worker/Representative (CHW/CHR)	0	0	3	28	58	69	74
Mental/Behavioral Health Professional (non-physician: LMHC, LCSW, LPCC, etc)	1	11	31	44	45	67	95
Certified Health Care Manager (FACHE)	0	0	0	0	0	0	0
Registered Health Information Technician (RHIT)	0	0	0	0	0	0	1
Case Manager	0	0	0	0	0	0	0
Other	11	101	255	487	721	919	1305

ECHO Participant Type

When it comes to participant category “Nursing professionals” (registered nurses, advanced practice nurses, etc..) are majorly involved in ECHO sessions compared to other types starting from inception.

ECHO Participant Variables

Year	No. of Individual Attendees	No. of Individual Facilitators	Grand Total	total times (attendees)	total times (facilitators)	Grand Total
2014	26	6	32	36	14	50
2015	252	34	286	757	302	1059
2016	574	61	635	1816	913	2729
2017	934	104	1038	2882	1156	4038
2018	1230	132	1362	4443	1575	6018
2019	2121	233	2354	7033	2178	9211
2020	2950	259	3209	14156	2477	16633

ECHO Participant Variables

The number of attendees and facilitators were constantly increasing from 2014 – 2020, as number of attendees increased from 26 to 2950 and number of facilitators increased from 6 to 259.

Number of Participating ECHO Organizations in Show-Me ECHO

Year	No. of Participating Organizations
2014	3
2015	60
2016	148
2017	192
2018	293
2019	414
2020	436

Number of Participating ECHO Organizations in Show-Me ECHO

Number of participating organizations per year increased from 3 to 436 from inception to 2020.

Type of ECHO

Year	In person (No. of Participants)	Audio (No. of Participants)	Video (No. of Participants)
2014	22	0	38
2015	349	32	625
2016	718	115	1390
2017	547	177	2616
2018	749	230	4343
2019	706	667	6893
2020	229	56	14969

Type of ECHO

Starting from 2014, ECHO programs have both in-person and video sessions, but video sessions are more compared to in-person or audio because the actual purpose of telemedicine/telehealth programs is to bring people from distance and underserved areas for participation in training, educational programs.

Number of Presentations and Presenters

Year	Presenters	Presentations
2014	1	2
2015	37	93
2016	76	252
2017	102	397
2018	148	451
2019	205	493
2020	193	355

Number of Presentations and Presenters

Number of presenters and presentations also got increased from 2014 to 2019 due to increase in attendance and sessions. But here we can observe decline in number for the year 2020, because of the unprecedented situations like COVID-19 pandemic, new ECHO sessions were started focusing on COVID topics. So, number of participants decreased in several other ECHO sessions and increased for COVID related ECHO programs.

Counties' Involvement across Missouri state

Year	Participants/Healthcare center counties (across Missouri)
2014	8
2015	40
2016	52
2017	66
2018	72
2019	102
2020	108

Involvement of Counties across Missouri

The number of counties involved in ECHO programs also increased from 8 in 2014 to 108 in 2020.

Detailed SMA & ARIMA calculation steps -

1. Testing stationarity of Data: (Augmented Dickey-Fuller test/Python)

Monthly Actual Attendance: (2015-2019)

Month	2014	2015	2016	2017	2018	2019
Jan	-	14	86	145	230	499
Feb	-	32	70	168	291	527
Mar	-	49	71	118	299	542
Apr	-	52	90	110	319	451
May	-	42	109	151	243	393
Jun	-	47	94	153	237	330
Jul	-	28	59	117	141	190
Aug	-	46	50	129	172	248
Sep	-	90	143	245	291	411
Oct	- (5)	91	155	203	304	489
Nov	- (26)	39	149	297	298	534
Dec	- (4)	25	114	232	237	416

Stationarity is an important concept when working with time series data. A stationary series is in which the properties like mean, variance and covariance do not vary with time. Before applying time-series analysis and forecasting predictions, it is important to test the stationarity of real time data, because usually maximum real time data would be non-stationary. There are several ways to test stationarity those are – visual test (through graphs) and statistical test (Augmented Dickey Fuller test [ADF] and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS), since statistical tests are more accurate, I chose ADF test.

Null Hypothesis: The series has a unit root, series is non-stationary, Alternate Hypothesis: The series has no unit root, series is stationary.

ADF Test: The Dickey Fuller test is a popular statistical test to verify the stationarity of the data and works through determining the presence of unit root in the series which are the reason for non-stationary. Test statistics value has to be negative, the more negative than critical values, the more data is stationary.

- If we fail to reject null hypothesis, we can say that the series is non-stationary.
- If we reject Null, and considered alternate hypothesis valid, we can say that the series is stationary.

Augmented Dickey-Fuller (ADF) Statistical test Results

Data point	ADF - Test Statistics	p-Value	Critical value ranges
Actual Values			1%: -3.575 5%: -2.924 10%: -2.600
Actual Values – 0 diff	3.153606	1.000000	
Actual Values – 1 diff	-2.646546	0.083754	
Actual Values – 2 diff	-5.126300	0.000012	

Results of ADF Test: The ADF gives the following results – test statistics, p value and the critical value at 1%, 5%, and 10% confidence intervals. For actual values I got positive

```
import pandas as pd
import numpy as np
from numpy import log
import statsmodels
import matplotlib.pyplot as plt
Dataframe = pd.read_csv('Moving Average 1.csv', index_col = 'Date',
parse_dates = True)
plt.plot(Dataframe['Actual Attendees'])
df_stationary = Dataframe.diff().dropna()
df_stationary2 = df_stationary.diff().dropna()
print(df_stationary2)
from statsmodels.tsa.stattools import adfuller
#adf_test = adfuller(Dataframe['Actual Attendees'])
#print(adf_test)
X = df_stationary2.values
#X = (log(X))
result = adfuller(X)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
if result[0] < result [4]['5%']:
    print ("Reject Null - time series is stationary")
else:
    print ("Failed to Reject Null - time series is Non-stationary")
```

ADF test statistics value and p-value greater than 0.05, means my data is non-stationary. Since it was non-stationary, checked by differentiating the actual values. For one differentiation of 60 observations data, the statistics test yields value of -2.64 which is not far negative even than the critical value of -2.92 at 95% level, so the null hypothesis of a unit root cannot be rejected at this point, means data is still non-stationary at this differentiation level. For two differentiations of 60 observations data, the statistics test yields value of -5.12 which is more negative than the critical value of -3.57 and less p value 0.000012 at 99% level the null hypothesis of a unit root can be rejected at this point, means data will become more stationary at this differentiation level.

2. Simple Moving Average Time series Forecasting process

For the conversion of non-stationary data to stationary as part of preprocessing of data, followed two differentiations, Differentiation 1: Differentiation through Moving Average (to make mean equal and stable), Differentiation 2: Seasonal differentiation (to make variance equal and stable).

Simple Moving Average Time Series Procedure

- a) Step: 1 – Collection and Preprocessing Data: Considered Quantitative monthly data about who attended ECHO sessions in particular month and number of attendees including facilitators from January 2015 to December 2019.

Monthly Actual Attendance (2015-2019)

Month	2015	2016	2017	2018	2019
Jan	14	86	145	230	499
Feb	32	70	168	291	527
Mar	49	71	118	299	542
Apr	52	90	110	319	451
May	42	109	151	243	393
Jun	47	94	153	237	330
Jul	28	59	117	141	190
Aug	46	50	129	172	248
Sep	90	143	245	291	411
Oct	91	155	203	304	489
Nov	39	149	297	298	534
Dec	25	114	232	237	416

- b) Step: 2 – Visualizing Data: To identify time series components such as trend, seasonality, and irregularity, visualized the data using line chart with markers and at the same point with visualizations observing the trends in actual data/numbers will be easy.

Timeseries of number of attendees in all ECHO Sessions 2015-2019

With this graph, found out that the data in early years are not stable in order of variations, sessions have less attendance, the reason could be that Telehealth or ECHO sessions are newly emerging health technology during that time. Also, we can observe that the number of participants is increasing with time period, and we may have more data in future which can help in accurate predictions.

- c) Step: 3 – Calculating Simple Moving Average: To smooth out the data, ironing/flatten out the up and downs (irregularities/seasonality).

Moving Average Calculation MA (12)

Year	Month	Actual Attendees	MA (12)				
2015	Jan	14			Jul	117	179.4167
	Feb	32			Aug	129	189.6667
	Mar	49			Sep	245	204.75
	Apr	52			Oct	203	222.1667
	May	42			Nov	297	229.8333
	Jun	47	46.25		Dec	232	236.8333
	Jul	28	52.25	2018	Jan	230	238.8333
	Aug	46	55.41667		Feb	291	242.4167
	Sep	90	57.25		Mar	299	246.25
	Oct	91	60.41667		Apr	319	254.6667
	Nov	39	66		May	243	254.75
	Dec	25	69.91667		Jun	237	255.1667
2016	Jan	86	72.5		Jul	141	277.5833
	Feb	70	72.83333		Aug	172	297.25
	Mar	71	77.25		Sep	291	317.5
	Apr	90	82.58333		Oct	304	328.5
	May	109	91.75		Nov	298	341
	Jun	94	99.16667		Dec	237	348.75
	Jul	59	104.0833	2019	Jan	499	352.8333
	Aug	50	112.25		Feb	527	359.1667
	Sep	143	116.1667		Mar	542	369.1667
	Oct	155	117.8333		Apr	451	384.5833
	Nov	149	121.3333		May	393	404.25
	Dec	114	126.25		Jun	330	419.1667
2017	Jan	145	131.0833		Jul	190	
	Feb	168	137.6667		Aug	248	
	Mar	118	146.1667		Sep	411	
	Apr	110	150.1667		Oct	489	
	May	151	162.5		Nov	534	
	Jun	153	172.3333		Dec	416	

- d) Step: 4 – Calculating Center Moving Average: In order to maintain proper association of moving average values to original data and also to get rid of seasonality and irregularity components.

Centered Simple Moving Average Calculation CMA (12)

Year	Month	Actual Attendees	MA (12)	CMA (12)					
2015	Jan	14				Jul	117	179.4167	184.5417
	Feb	32				Aug	129	189.6667	197.2083
	Mar	49				Sep	245	204.75	213.4583
	Apr	52				Oct	203	222.1667	226
	May	42				Nov	297	229.8333	233.3333
	Jun	47	46.25	49.25		Dec	232	236.8333	237.8333
	Jul	28	52.25	53.83333	2018	Jan	230	238.8333	240.625
	Aug	46	55.41667	56.33333		Feb	291	242.4167	244.3333
	Sep	90	57.25	58.83333		Mar	299	246.25	250.4583
	Oct	91	60.41667	63.20833		Apr	319	254.6667	254.7083
	Nov	39	66	67.95833		May	243	254.75	254.9583
	Dec	25	69.91667	71.20833		Jun	237	255.1667	266.375
2016	Jan	86	72.5	72.66667		Jul	141	277.5833	287.4167
	Feb	70	72.83333	75.04167		Aug	172	297.25	307.375
	Mar	71	77.25	79.91667		Sep	291	317.5	323
	Apr	90	82.58333	87.16667		Oct	304	328.5	334.75
	May	109	91.75	95.45833		Nov	298	341	344.875
	Jun	94	99.16667	101.625		Dec	237	348.75	350.7917
	Jul	59	104.0833	108.1667	2019	Jan	499	352.8333	356
	Aug	50	112.25	114.2083		Feb	527	359.1667	364.1667
	Sep	143	116.1667	117		Mar	542	369.1667	376.875
	Oct	155	117.8333	119.5833		Apr	451	384.5833	394.4167
	Nov	149	121.3333	123.7917		May	393	404.25	411.7083
	Dec	114	126.25	128.6667		Jun	330	419.1667	
2017	Jan	145	131.0833	134.375		Jul	190		
	Feb	168	137.6667	141.9167		Aug	248		
	Mar	118	146.1667	148.1667		Sep	411		
	Apr	110	150.1667	156.3333		Oct	489		
	May	151	162.5	167.4167		Nov	534		
	Jun	153	172.3333	175.875		Dec	416		

Timeseries of number of attendees in all ECHO Sessions with CMA 2015-2019

- e) Step: 5 – Calculating difference between original values and values without seasonal and irregular components (to identify actual variation in values. (By dividing original value with CMA))

St, It (Seasonality and Irregularity) Calculation

Year	Month	Yt	MA (12)	CMA(12)	St, It						
2015	Jan	14					Jul	117	179.4167	184.5417	0.634003
	Feb	32					Aug	129	189.6667	197.2083	0.654131
	Mar	49					Sep	245	204.75	213.4583	1.147765
	Apr	52					Oct	203	222.1667	226	0.89823
	May	42					Nov	297	229.8333	233.3333	1.272857
	Jun	47	46.25	49.25	0.954315		Dec	232	236.8333	237.8333	0.975473
	Jul	28	52.25	53.83333	0.520124	2018	Jan	230	238.8333	240.625	0.955844
	Aug	46	55.41667	56.33333	0.816568		Feb	291	242.4167	244.3333	1.190996
	Sep	90	57.25	58.83333	1.529745		Mar	299	246.25	250.4583	1.193811
	Oct	91	60.41667	63.20833	1.439684		Apr	319	254.6667	254.7083	1.252413
	Nov	39	66	67.95833	0.573881		May	243	254.75	254.9583	0.953097
	Dec	25	69.91667	71.20833	0.351083		Jun	237	255.1667	266.375	0.889723
2016	Jan	86	72.5	72.66667	1.183486		Jul	141	277.5833	287.4167	0.490577
	Feb	70	72.83333	75.04167	0.932815		Aug	172	297.25	307.375	0.559577
	Mar	71	77.25	79.91667	0.888425		Sep	291	317.5	323	0.900929
	Apr	90	82.58333	87.16667	1.032505		Oct	304	328.5	334.75	0.90814
	May	109	91.75	95.45833	1.141859		Nov	298	341	344.875	0.864081
	Jun	94	99.16667	101.625	0.924969		Dec	237	348.75	350.7917	0.675615
	Jul	59	104.0833	108.1667	0.545455	2019	Jan	499	352.8333	356	1.401685
	Aug	50	112.25	114.2083	0.437796		Feb	527	359.1667	364.1667	1.44714
	Sep	143	116.1667	117	1.222222		Mar	542	369.1667	376.875	1.438143
	Oct	155	117.8333	119.5833	1.296167		Apr	451	384.5833	394.4167	1.143461
	Nov	149	121.3333	123.7917	1.203635		May	393	404.25	411.7083	0.954559
	Dec	114	126.25	128.6667	0.88601		Jun	330	419.1667		
2017	Jan	145	131.0833	134.375	1.07907		Jul	190			
	Feb	168	137.6667	141.9167	1.183793		Aug	248			

	Mar	118	146.1667	148.1667	0.7964		Sep	411			
	Apr	110	150.1667	156.3333	0.703625		Oct	489			
	May	151	162.5	167.4167	0.901941		Nov	534			
	Jun	153	172.3333	175.875	0.869936		Dec	416			

- f) Step: 6 – Quantifying Seasonality: To eliminate/get rid of irregularity (It), per each month (average of same month in every year)

Seasonal Component (St) Calculation

Month	St
Jan	1.16
Feb	1.19
Mar	1.08
Apr	1.03
May	0.99
Jun	0.91
Jul	0.55
Aug	0.62
Sep	1.20
Oct	1.18
Nov	0.98
Dec	0.72

- g) Step: 7 – De-seasonalization: dividing original value with seasonality (St)

De-seasonalized Data

Year	Month	Actual Attendees	MA (12)	CMA (12)	St, It	St	De-seasonalize
2015	Jan	14				1.16	12.12098766
	Feb	32				1.19	26.92048249
	Mar	49				1.08	45.40421481
	Apr	52				1.03	50.33877985
	May	42				0.99	42.51596438
	Jun	47	46.25	49.25	0.954315	0.91	51.66335191
	Jul	28	52.25	53.83333	0.520124	0.55	51.13785087
	Aug	46	55.41667	56.33333	0.816568	0.62	74.55211676
	Sep	90	57.25	58.83333	1.529745	1.20	74.98967269
	Oct	91	60.41667	63.20833	1.439684	1.18	77.27254114
	Nov	39	66	67.95833	0.573881	0.98	39.85229589
	Dec	25	69.91667	71.20833	0.351083	0.72	34.62387397
2016	Jan	86	72.5	72.66667	1.183486	1.16	74.45749562

	Feb	70	72.83333	75.04167	0.932815	1.19	58.88855544
	Mar	71	77.25	79.91667	0.888425	1.08	65.78978064
	Apr	90	82.58333	87.16667	1.032505	1.03	87.12481128
	May	109	91.75	95.45833	1.141859	0.99	110.3390504
	Jun	94	99.16667	101.625	0.924969	0.91	103.3267038
	Jul	59	104.0833	108.1667	0.545455	0.55	107.7547572
	Aug	50	112.25	114.2083	0.437796	0.62	81.03490952
	Sep	143	116.1667	117	1.222222	1.20	119.1502577
	Oct	155	117.8333	119.5833	1.296167	1.18	131.6180646
	Nov	149	121.3333	123.7917	1.203635	0.98	152.2562074
	Dec	114	126.25	128.6667	0.88601	0.72	157.8848653
2017	Jan	145	131.0833	134.375	1.07907	1.16	125.5388008
	Feb	168	137.6667	141.9167	1.183793	1.19	141.3325331
	Mar	118	146.1667	148.1667	0.7964	1.08	109.3407622
	Apr	110	150.1667	156.3333	0.703625	1.03	106.4858805
	May	151	162.5	167.4167	0.901941	0.99	152.8550148
	Jun	153	172.3333	175.875	0.869936	0.91	168.1806988
	Jul	117	179.4167	184.5417	0.634003	0.55	213.6831626
	Aug	129	189.6667	197.2083	0.654131	0.62	209.0700666
	Sep	245	204.75	213.4583	1.147765	1.20	204.1385534
	Oct	203	222.1667	226	0.89823	1.18	172.3772072
	Nov	297	229.8333	233.3333	1.272857	0.98	303.490561
	Dec	232	236.8333	237.8333	0.975473	0.72	321.3095504
2018	Jan	230	238.8333	240.625	0.955844	1.16	199.1305116
	Feb	291	242.4167	244.3333	1.190996	1.19	244.8081376
	Mar	299	246.25	250.4583	1.193811	1.08	277.058372
	Apr	319	254.6667	254.7083	1.252413	1.03	308.8090533
	May	243	254.75	254.9583	0.953097	0.99	245.9852225
	Jun	237	255.1667	266.375	0.889723	0.91	260.5152001
	Jul	141	277.5833	287.4167	0.490577	0.55	257.5156062
	Aug	172	297.25	307.375	0.559577	0.62	278.7600888
	Sep	291	317.5	323	0.900929	1.20	242.4666084
	Oct	304	328.5	334.75	0.90814	1.18	258.1412363
	Nov	298	341	344.875	0.864081	0.98	304.5124147
	Dec	237	348.75	350.7917	0.675615	0.72	328.2343252
2019	Jan	499	352.8333	356	1.401685	1.16	432.0266316
	Feb	527	359.1667	364.1667	1.44714	1.19	443.346696
	Mar	542	369.1667	376.875	1.438143	1.08	502.2262128
	Apr	451	384.5833	394.4167	1.143461	1.03	436.5921099
	May	393	404.25	411.7083	0.954559	0.99	397.8279524
	Jun	330	419.1667			0.91	362.7426837
	Jul	190				0.55	347.0068452
	Aug	248				0.62	401.9331512

	Sep	411				1.20	342.4528386
	Oct	489				1.18	415.233765
	Nov	534				0.98	545.6698975
	Dec	416				0.72	576.1412628

h) Step: 8 – Calculating Trend components: with series of periods (t), for this finding out intercept and values of t through Simple Linear Regression on original data

Simple Moving Average - Regression Analysis

SUMMARY OUTPUT

<i>Regression Statistics</i>	
Multiple R	0.937134
R Square	0.878221
Adjusted R Square	
Standard Error	0.876121
Observations	50.96919
	60

<i>ANOVA</i>					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	1086609	1086609	418.2711133	3.36661E-28
Residual	58	150675.8	2597.858		
Total	59	1237285			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-29.2074	13.32643	-2.191689	0.032430633	-55.8831387	-2.531647	-55.88314	-2.531647
t	7.770711	0.379955	20.45168	3.36661E-28	7.01014886	8.531273	7.010149	8.531273

Trend Component Calculation (Tt)

t	Year	Month	Actual Attendees	MA (12)	CMA (12)	St, It	St	Deseasonalize	Tt
1	2015	Jan	14				1.16	12.12098766	-21.4367
2		Feb	32				1.19	26.92048249	-13.666
3		Mar	49				1.08	45.40421481	-5.89526
4		Apr	52				1.03	50.33877985	1.87545
5		May	42				0.99	42.51596438	9.646161
6		Jun	47	46.25	49.25	0.954315	0.91	51.66335191	17.41687
7		Jul	28	52.25	53.83333	0.520124	0.55	51.13785087	25.18758
8		Aug	46	55.41667	56.33333	0.816568	0.62	74.55211676	32.95829
9		Sep	90	57.25	58.83333	1.529745	1.20	74.98967269	40.729

10		Oct	91	60.41667	63.20833	1.439684	1.18	77.27254114	48.49972
11		Nov	39	66	67.95833	0.573881	0.98	39.85229589	56.27043
12		Dec	25	69.91667	71.20833	0.351083	0.72	34.62387397	64.04114
13	2016	Jan	86	72.5	72.66667	1.183486	1.16	74.45749562	71.81185
14		Feb	70	72.83333	75.04167	0.932815	1.19	58.88855544	79.58256
15		Mar	71	77.25	79.91667	0.888425	1.08	65.78978064	87.35327
16		Apr	90	82.58333	87.16667	1.032505	1.03	87.12481128	95.12398
17		May	109	91.75	95.45833	1.141859	0.99	110.3390504	102.8947
18		Jun	94	99.16667	101.625	0.924969	0.91	103.3267038	110.6654
19		Jul	59	104.0833	108.1667	0.545455	0.55	107.7547572	118.4361
20		Aug	50	112.25	114.2083	0.437796	0.62	81.03490952	126.2068
21		Sep	143	116.1667	117	1.222222	1.20	119.1502577	133.9775
22		Oct	155	117.8333	119.5833	1.296167	1.18	131.6180646	141.7482
23		Nov	149	121.3333	123.7917	1.203635	0.98	152.2562074	149.519
24		Dec	114	126.25	128.6667	0.88601	0.72	157.8848653	157.2897
25	2017	Jan	145	131.0833	134.375	1.07907	1.16	125.5388008	165.0604
26		Feb	168	137.6667	141.9167	1.183793	1.19	141.3325331	172.8311
27		Mar	118	146.1667	148.1667	0.7964	1.08	109.3407622	180.6018
28		Apr	110	150.1667	156.3333	0.703625	1.03	106.4858805	188.3725
29		May	151	162.5	167.4167	0.901941	0.99	152.8550148	196.1432
30		Jun	153	172.3333	175.875	0.869936	0.91	168.1806988	203.9139
31		Jul	117	179.4167	184.5417	0.634003	0.55	213.6831626	211.6846
32		Aug	129	189.6667	197.2083	0.654131	0.62	209.0700666	219.4554
33		Sep	245	204.75	213.4583	1.147765	1.20	204.1385534	227.2261
34		Oct	203	222.1667	226	0.89823	1.18	172.3772072	234.9968
35		Nov	297	229.8333	233.3333	1.272857	0.98	303.490561	242.7675
36		Dec	232	236.8333	237.8333	0.975473	0.72	321.3095504	250.5382
37	2018	Jan	230	238.8333	240.625	0.955844	1.16	199.1305116	258.3089
38		Feb	291	242.4167	244.3333	1.190996	1.19	244.8081376	266.0796
39		Mar	299	246.25	250.4583	1.193811	1.08	277.058372	273.8503
40		Apr	319	254.6667	254.7083	1.252413	1.03	308.8090533	281.621
41		May	243	254.75	254.9583	0.953097	0.99	245.9852225	289.3918
42		Jun	237	255.1667	266.375	0.889723	0.91	260.5152001	297.1625
43		Jul	141	277.5833	287.4167	0.490577	0.55	257.5156062	304.9332
44		Aug	172	297.25	307.375	0.559577	0.62	278.7600888	312.7039
45		Sep	291	317.5	323	0.900929	1.20	242.4666084	320.4746
46		Oct	304	328.5	334.75	0.90814	1.18	258.1412363	328.2453
47		Nov	298	341	344.875	0.864081	0.98	304.5124147	336.016
48		Dec	237	348.75	350.7917	0.675615	0.72	328.2343252	343.7867
49	2019	Jan	499	352.8333	356	1.401685	1.16	432.0266316	351.5574
50		Feb	527	359.1667	364.1667	1.44714	1.19	443.346696	359.3281
51		Mar	542	369.1667	376.875	1.438143	1.08	502.2262128	367.0989
52		Apr	451	384.5833	394.4167	1.143461	1.03	436.5921099	374.8696

53		May	393	404.25	411.7083	0.954559	0.99	397.8279524	382.6403
54		Jun	330	419.1667			0.91	362.7426837	390.411
55		Jul	190				0.55	347.0068452	398.1817
56		Aug	248				0.62	401.9331512	405.9524
57		Sep	411				1.20	342.4528386	413.7231
58		Oct	489				1.18	415.233765	421.4938
59		Nov	534				0.98	545.6698975	429.2645
60		Dec	416				0.72	576.1412628	437.0353

i) Step: 9 – MA - Prediction values:

SMA - Prediction values for past attendance (2015-2019)

Month	2014	2015	2016	2017	2018	2019
Jan	-	-25	83	191	298	406
Feb	-	-16	95	205	316	427
Mar	-	-6	94	195	296	396
Apr	-	2	98	195	291	387
May	-	10	102	194	286	378
Jun	-	16	101	186	270	355
Jul	-	14	65	116	167	218
Aug	-	20	78	135	193	250
Sep	-	49	161	273	385	497
Oct	NaN	57	167	277	387	496
Nov	NaN	55	146	238	329	420
Dec	NaN	46	114	181	248	316

SMA – Actual attendance Vs Predicted Values (2015 – 2019)

3. ARIMA Time series Forecasting process

Auto Regressive Integrated Moving Average models consist of specifying conditional mean of process, which are stochastic models specified as sum of simple or multiple linear relationships with lagged level or differentiation of variable model errors and constant mean or drift.

Differenced first-order autoregressive model consist of difference forecast equal to determine simple linear relationship with previous period data difference plus a constant drift. Considered ARIMA (1,1,0) with constant.

As a Main formula:
$$Y_{tf} = C + Y_{t-1} + AR(1) * ((Y_{t-1}) - (Y_{t-2}))$$

Current period forecast is equal to a constant drift plus previous periods data plus an autoregressive coefficient multiplied by the difference between (previous period – second previous period) data.

- Differentiation 1: DY_t – Differentiated data (Current value – Previous value)
- Differentiation 2: Y_{tf} – (previous period – second previous period)

ARIMA – Differentiation of training range data

Year	Month	Yt	DYt				
2015	Jan	14	0		Jul	117	-36
	Feb	32	18		Aug	129	12
	Mar	49	17		Sep	245	116
	Apr	52	3		Oct	203	-42
	May	42	-10		Nov	297	94
	Jun	47	5		Dec	232	-65
	Jul	28	-19	2018	Jan	230	-2
	Aug	46	18		Feb	291	61
	Sep	90	44		Mar	299	8
	Oct	91	1		Apr	319	20
	Nov	39	-52		May	243	-76
	Dec	25	-14		Jun	237	-6
2016	Jan	86	61		Jul	141	-96
	Feb	70	-16		Aug	172	31
	Mar	71	1		Sep	291	119
	Apr	90	19		Oct	304	13
	May	109	19		Nov	298	-6
	Jun	94	-15		Dec	237	-61
	Jul	59	-35	2019	Jan	499	262

	Aug	50	-9		Feb	527	28
	Sep	143	93		Mar	542	15
	Oct	155	12		Apr	451	-91
	Nov	149	-6		May	393	-58
	Dec	114	-35		Jun	330	-63
2017	Jan	145	31		Jul	190	-140
	Feb	168	23		Aug	248	58
	Mar	118	-50		Sep	411	163
	Apr	110	-8		Oct	489	78
	May	151	41		Nov	534	45
	Jun	153	2		Dec	416	-118

Table 23: ARIMA – Linear Regression Analysis of differentiated values

SUMMARY OUTPUT

<i>Regression Statistics</i>	
Multiple R	0.897544
R Square	0.805586
Adjusted R Square	0.802175
Standard Error	64.7306
Observations	59

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	989639.8	989639.8	236.1881	6.25E-22
Residual	57	238832.9	4190.05		
Total	58	1228473			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	25.79207	14.20548	1.815642	0.074686	-2.65391	54.23805	-2.65391	54.23805
t-1	0.902539	0.058727	15.36841	6.25E-22	0.78494	1.020137	0.78494	1.020137

	ARIMA (1,1,0) C
Constant Drift	0.036
AR (1)	0.902

ARIMA – Prediction Values for actual data (2015 – 2019)

Ytf – Forecasting values for actual data

Year	Month	Yt	DYt	Ytf					
2015	Jan	14	0	14		Jul	117	-36	154.84
	Feb	32	18	32		Aug	129	12	84.564

	Mar	49	17	48.272		Sep	245	116	139.86
	Apr	52	3	64.37		Oct	203	-42	349.668
	May	42	-10	54.742		Nov	297	94	165.152
	Jun	47	5	33.016		Dec	232	-65	381.824
	Jul	28	-19	51.546	2018	Jan	230	-2	173.406
	Aug	46	18	10.898		Feb	291	61	228.232
	Sep	90	44	62.272		Mar	299	8	346.058
	Oct	91	1	129.724		Apr	319	20	306.252
	Nov	39	-52	91.938		May	243	-76	337.076
	Dec	25	-14	-7.868		Jun	237	-6	174.484
2016	Jan	86	61	12.408		Jul	141	-96	231.624
	Feb	70	-16	141.058		Aug	172	31	54.444
	Mar	71	1	55.604		Sep	291	119	199.998
	Apr	90	19	71.938		Oct	304	13	398.374
	May	109	19	107.174		Nov	298	-6	315.762
	Jun	94	-15	126.174		Dec	237	-61	292.624
	Jul	59	-35	80.506	2019	Jan	499	262	182.014
	Aug	50	-9	27.466		Feb	527	28	735.36
	Sep	143	93	41.918		Mar	542	15	552.292
	Oct	155	12	226.922		Apr	451	-91	555.566
	Nov	149	-6	165.86		May	393	-58	368.954
	Dec	114	-35	143.624		Jun	330	-63	340.72
2017	Jan	145	31	82.466		Jul	190	-140	273.21
	Feb	168	23	172.998		Aug	248	58	63.756
	Mar	118	-50	188.782		Sep	411	163	300.352
	Apr	110	-8	72.936		Oct	489	78	558.062
	May	151	41	102.82		Nov	534	45	559.392
	Jun	153	2	188.018		Dec	416	-118	574.626

ARIMA - Prediction values for past attendance (2015-2019)

Month	2014	2015	2016	2017	2018	2019
Jan	-	14	12	82	173	182
Feb	-	32	141	173	228	735
Mar	-	48	56	189	346	552
Apr	-	64	72	73	306	556
May	-	55	107	103	337	369
Jun	-	33	126	188	174	341
Jul	-	52	81	155	232	273
Aug	-	11	27	85	54	64
Sep	-	62	42	140	200	300
Oct	NaN	130	227	350	398	558
Nov	NaN	92	166	165	316	559
Dec	NaN	-8	144	382	293	575

ARIMA – Actual attendance Vs Predicted Values (2015 – 2019)

4. Comparison of SMA and ARIMA prediction values

- Tested both SMA and ARIMA on actual data and selected moving average model as effective based on R-square value and p-value. This step is to select appropriate time series analysis type for forecasting, compared R-square value and p-value through basic regression test. Selected Moving average model which got high R-square value 0.87 and less p - value 3.36E-28 at 95% confidence interval as better model for forecasting.
- In evaluating performance metrics (error measures) in either machine learning regression, forecasting techniques and prognostics, scale-dependent measures like Mean Square Error (MSE), Mean Absolute Error (MAE) and measures based on percentage errors such as Mean Absolute Percentage Error (MAPE) are widely used due to their high efficiency. Tested through calculating error values for actual values and predicted values of monthly data from Jan 2015- Jan 2019 for both Simple Moving Average model and ARIMA model.

- a) Mean Absolute Error – Average of the forecast error values, where all the forecast error values are forced to be positive.

$$\text{MAE/MAD} = \text{ABS (Actual value – Predicted value)}$$

- b) Mean Square Error – Average of squared forecast error values to force them to be positive and it has the effect of putting more weight on large errors.

$$\text{MSE} = (\text{Actual value – predicted value})^2$$

- c) Mean Absolute Percentage Error – Measures the size of the error in percentage terms and expresses accuracy as a percentage of the error.

$$\text{MAPE} = \text{ABS (Actual value – Predicted value)}/\text{Actual value}$$

Comparison of Simple Moving Average and ARIMA forecasting models

Error tests	MA Values	ARIMA Values	Reference Values
MAE/MAD	38.90	61.82	0 to ∞ (Lower values are better)
MSE	2552.15	7198.88	-10,000 - +10,000
MAPE	32.9%	37.7%	< 10% is Excellent, < 20% is Good
R-square value	0.878	0.805	
p-value	3.36E-28	6.25E-22	

5. Forecasting values (2020 – 2025)

Future Predicted Attendance (Simple Moving Average Forecasting) (2020-2025)

Month	2020	2021	2022	2023	2024	2025
Jan	514	621	729	837	945	1052
Feb	538	649	760	871	981	1092
Mar	497	597	698	799	899	1000
Apr	484	580	676	773	869	965
May	470	562	654	746	839	931
Jun	440	525	610	694	779	864
Jul	269	320	371	422	473	524
Aug	308	366	423	481	538	596
Sep	608	720	832	944	1056	1168
Oct	606	716	826	936	1045	1155
Nov	511	603	694	785	876	968
Dec	383	450	518	585	652	720

Timeseries of number of attendees in all ECHO Sessions – Actual (2015 – 2019) Vs SMA Forecasting (2020-2025)