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ARIMA based Forecasting of an Integrated Model of 360-Degree Feedback for Administrative Staff of HEIs

***Richard kodi,** Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development Kumasi, Ghana
Rosemary Adu-Poku, Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development Kumasi, Ghana
Adwoa Serwaa Karikari, Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development Kumasi, Ghana

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ABSTRACT

This research focuses on enhancing the performance of a novel model called the Integrated Model of 360-degree feedback for Administrative Staff in Higher Education Institutions (HEIs). The study employs a time series approach to analyse historical data from this model to inform future strategic decisions. The selected ARIMA models demonstrated high forecasting accuracy, with Root Mean Square Errors (RMSE) approaching negligible values (0.12 for job performance, 0.04 for change in appraisal satisfaction, and 0.05 for job capability).
Specifically, the ARIMA (1, 0, 1) model predicts moderate job performance, the ARIMA (0, 1, 3) model suggests relatively low appraisal satisfaction, and the ARIMA (0, 0, 4) model indicates a moderate job capability level, assuming other factors remain constant. The study explores the interconnectedness of data between appraisal satisfaction, job capability, and job performance, highlighting the potential for improved performance within the 360-degree feedback framework.
In summary, this research constructs ARIMA models to forecast job performance, appraisal satisfaction, and job capability, demonstrating their effectiveness in the short term. Utilizing precise ARIMA models tailored to these performance indicators has the potential to significantly enhance forecasting accuracy and subsequently boost employee productivity within the Integrated Model of the 360-degree feedback framework.

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Corresponding author's email address: lou4rich@gmail.com
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Introduction

In the era of globalization, new fronts of competition are emerging, attracting the attention of not only institutions boasting high bibliometric scores, substantial budgets, research accolades, and esteemed international standing. In the past decade, the higher education sector, akin to many other non-profit industries, has encountered a multitude of fundamental challenges. Historically, education was perceived as a public good, dispensed by non-profit entities driven by distinct societal missions within a competitive open market.

The international knowledge marketplace is currently experiencing escalated competition, resulting in a significant reshaping of the Higher Education Institutions (HEIs) landscape. Although education was previously solely within the realm of government regulation, it has now evolved into a worldwide service offered by private companies. The noticeable uptick in queries about methods to enhance workforce efficiency within the higher education sphere highlights the urgent necessity for HEIs to formulate successful strategies for addressing these issues. To excel in this changing scenario, HEIs must assimilate business models inherent in profit-oriented enterprises, which encompasses the integration of performance management principles.

The adoption of Performance Appraisals (PAs) among staff is becoming increasingly prominent across Higher Education Institutions (HEIs) worldwide. PAs serve as a mechanism to guarantee the provision of excellent academic services and to adhere to the standards established by local and global quality assurance and academic accreditation organizations. It's unquestionable that an organization's most valuable resource and significant corporate dedication reside within its workforce (Vithana et al., 2021).

The skills and proficiencies of employees hold substantial sway over a company's productivity, financial sustainability, and long-term feasibility (International Labour Conference, 2008).

To achieve organizational goals and maintain profitability, assessing employee performance and creating efficient management strategies are of paramount significance. Performance appraisals hold a crucial role in achieving accurate cost analysis and proficient staff management (Jabeen, 2011). This integral element outlines individuals' abilities and potentials. Insights drawn from appraisals can inform individuals about new initiatives, strategies, and objectives (Hamidi, 2010).

Performance management encompasses a series of organizational techniques and procedures aimed at enhancing the creation and execution of corporate strategies (Ariyachandra and Frolick, 2008, pp.114). The careful oversight of individual employee performance emerges as a pivotal factor. The continual competitiveness of Higher Education Institutions (HEIs) could hinge on the thorough effectiveness of this management facet. The management of individual employee performance becomes critical. The enduring competitiveness of HEIs might rely on the overall efficacy of this management function. One of the most debated subjects in business intelligence, and among the top ten technological advancements influencing corporate management, is performance management.

A fundamental necessity for all organizations involves the regular evaluation of their employees, with the goal of gauging their productivity and identifying areas for enhancement in staff development endeavours. Managing employee performance acts as a driving force for boosting effectiveness at both the organizational and individual levels.

This strategy entails defining an organization's aspirations, transforming them into specific individual goals, and carrying out frequent assessments of these goals. Through this framework, performance management offers a carefully organized and effective managerial methodology, particularly when providing public services.

An ineffective employee appraisal scheme, characterized by ambiguity, leaves employees unaware of how to contribute to the mission of the Institutions. In such instances, a lack of clarity can lead to a dearth of development or advancement. An unjust employee appraisal system has the potential to dampen employees' enthusiasm regarding the institution's future, resulting in reduced motivation and diminished performance levels (Muthiani, 2021). These deficiencies within the appraisal procedure can lead to adverse consequences for administrative performance, encompassing areas like leadership, office management abilities, personal efficacy, conflict resolution, planning, project management, and utilization of office technology. Furthermore, these shortcomings might trigger frustration and contribute to the erosion of positive morale (Van Thiel and Leeuw, 2002).

Performance appraisal systems lacking a well-defined structure, especially when feedback is lacking, tend to be reactive rather than proactive. Frequently, employees only hear from upper management or supervisors in situations involving mistakes, which perpetuates a dynamic that erodes employee confidence (Muthiani, 2021). In contrast, a clearly communicated and precisely outlined appraisal system relies on substantiated data and thoroughly documented records.

According to Kochanski, Alderson and Sorenson (2005), performance management still has a long way to go in most organizations around the world in terms of meeting their tasks and objectives. Managing staff in an academic setting necessitates the use of strategic responses for managing diversity. Many firms continue to have issues with their performance measurement systems. Implementation problems lead to the "dark side of measurement," a negative reaction to measurement generated by sensitivity or fear of measurement because it is seen to be biased against individuals (Andy Neely *et al.*, 2002).

Envisioning changes in the business environment, which encompasses shifts in sales, expenditures, profits, and losses, requires researchers to employ a range of methodologies and approaches. The aim of business forecasting is to develop more effective strategies based on accurate predictions, in order to prevent potential setbacks or liabilities. This predictive process assists businesses in formulating data-driven strategies and enhancing their decision-making across all aspects of the business. Grounded in assessments of current market conditions and projections of future market dynamics, financial and operational choices are crafted. Historical data is gathered and analyzed to identify patterns that can be utilized for predicting future trends and shifts. Forecasting empowers your business to be proactive rather than reactive.

While widely practiced in fields such as finance and meteorology, the current body of literature lacks comprehensive explorations into the modeling and prediction of performance appraisal models in the context of performance management. Notable instances include studies by Lidiema (2017), Fwaga et al. (2017), and Uwilingiyimana et al. (2015), which focused on modeling and predicting inflation trends in Kenya. Similarly, Sideratos and Hatziargyriou (2007) delved into statistical methods for forecasting wind power.

Surprisingly, within the sphere of performance management, no efforts have been dedicated to forecasting Performance Appraisal models using a range of modeling techniques.
This study sets itself apart by employing the ARIMA approach to model and forecast the integrated 360-Degree Performance Appraisal within Higher Education Institutions (HEIs). Taking the University of Education, Winneba Ghana as a case study, the researchers ingeniously developed an Integrated Model of 360-Degree Feedback. This model acts as a valuable resource to enhance the efficiency of administrative staff within HEIs and improve the quality of academic services. It accomplishes this by seamlessly integrating the principles of the 360-Degree feedback appraisal method.

Autoregressive Integrated Moving Average (ARIMA)

ARIMA statistical analysis model employs time series data to primarily improve understanding of the data set or to forecast likely trends in the future. Due to their simplicity in application and comprehension, linear models have drawn a lot of attention from researchers over the past few decades. Forecasting demand, cryptocurrency, monthly sales results, and annual crop yields transactions are all common uses for time series forecasting models.

Fig. 1 The Use Cases of Time Series Forecasting.

Kurawarwala and Matsuo (1998) employed historical data to identify the seasonal fluctuations in demand. The models were then validated by assessing forecast accuracy within the framework of the autoregressive moving average hypothesis. In an enhancement of Miller and Williams' (2003) research, Hyndman (2004) explored various seasonal ARIMA relationships that relate trend and seasonality. The conventional ARIMA model's static parameters are perceived as the primary challenge in forecasting highly variable seasonal demand in such scenarios. Additionally, a drawback of the traditional ARIMA method is its requirement for a substantial number of observations to identify the best-fit model for a data series.

ARIMA forecasting has the primary advantage of requiring only relevant data from the time series under consideration. To begin, this feature is useful for predicting a wide variety of time series. Furthermore, this eliminates a potential problem with multivariate models.

Third, multivariate models may experience problems with timely data. As a result, another source of forecast uncertainty is introduced because the forecasts produced by this model are conditional forecasts based on projections of omitted observations. This scenario occurs when a sizable structural model is constructed using variables, like wage data, that are only released with a significant lag. ARIMA models, however, have shown to be quite trustworthy, particularly for forecasting short-term inflation. In terms of short-run prediction, ARIMA models typically outperform more intricate structural models.

ARIMA Forecasting in Practice

Some processes demonstrate cumulative impacts that can lead to changes in the patterns of time series. For example, the interaction between supply and consumption consistently affects stock levels. However, the average stock level is predominantly influenced by the gradual accumulation of small changes within inventories over time. It's crucial to acknowledge that while short-term stock prices may experience significant fluctuations around this average, the long-term trend remains relatively stable. An integrated process signifies a time series that reflects the overall effect of an activity.

In cases where observations are gathered at different time points, discrepancies within these observations might seem minimal or even exhibit fluctuations around a consistent value, even when the series itself demonstrates erratic behavior. In the context of statistical analysis, ensuring the stationarity of the variation series within an integrated process holds crucial importance. Integrated processes provide a framework for dealing with non-stationary series. This chapter delineates a comprehensive methodology for ARIMA modeling and forecasting. The visual representation of this approach is depicted in Figure 1. It's important to understand that this process is not strictly linear; it may involve iterative cycles based on insights from diagnostic evaluations and forecasting phases. The first step entails gathering the data intended for forecasting and subjecting it to both statistical and graphical analyses. The next phase requires assessing whether differencing is required or if the data demonstrate stationarity. Once stationarity is achieved, the suitable ARMA model is selected and estimated.

In this context, two distinct methods are utilized to identify relevant models: the criteria based on penalty functions and the Box-Jenkins methodology. Both of these approaches are taken into consideration to ascertain the fitting model. Any discovered model must go through several diagnostic modelling including sensitivity analysis and a variety of diagnostic checks (often based on analyzing the residuals).

Once a model or a set of models is selected, the next step entails forecasting the time series using these chosen models. It is recommended to evaluate the forecast by comparing it with actual data to assess the model's predictive accuracy. An error that can occur during the identification phase of ARIMA modeling is overfitting the model. While overfitting might improve the model's explanatory performance within the dataset, it could potentially result in reduced predictive ability outside the dataset compared to a more restrained model.

Hence, if a model with an extensive array of Moving Average (MA) and AutoRegressive (AR) lags yields unsatisfactory forecasting outcomes, it might be advisable to revert to the model identification phase and search for an alternative model that offers a more balanced and economical approach.

Methodology

Many researchers and industry executives believe that mathematical models must be simple and easy to use to evaluate performance in real-world situations (Wong and Wong, 2008). This paper describes the necessary and sufficient conditions for developing extensions to the developed performance appraisal framework.

Again, it demonstrates how mathematical models were used to forecast an Integrated Model of 360-Degree Feedback to be adopted by HEIs by using historical data collected from July 1, 2020, to December 12, 2021, to mitigate other risk factors associated with the Integrated Model of 360-Degree Feedback. On a Likert scale of 1 to 5, with 1 representing strongly disagreement and 5 representing strongly agreement, the respondents indicated their level of agreement or disagreement. As a result, the overall mean score of each construct was interpreted as follows: 1 = Very low, 2 = Low, 3 = Moderate, 4 = High and 5 = Very High.

The ARIMA Model encompasses three stages. The initial stage is the Identification Stage, during which the values of "p," "D," and "q" are determined. Stationarity or "D" is established using tools such as line graphs, correlograms, and formal tests like the Augmented Dickey-Fuller, Phillips-Perron, and KPSS tests (Bharatpur, 2022). The calculation of "P" relies on the Partial Autocorrelation Function (PACF), while "q" is computed using the Autocorrelation Function

(ACF).

It's important to note that selecting the appropriate AR and MA components lacks precise guidelines, making personal judgment a crucial factor. Experience in this context holds significant weight.

The second stage involves estimation. The optimal ARIMA model is estimated through coefficient approximations and model evaluation metrics such as the Akaike Information Criterion and Hannan-Quinn Information Criterion. The model with the highest coefficients and the lowest values for the model criteria will be the most suitable. The third and final stage includes Diagnostics and Forecasting. The model is diagnosed and fine-tuned for forecasting based on criteria like a relatively small BIC (Bayesian or Schwarz Information Criterion), a relatively high adjusted R2, and the absence of residual autocorrelation. Figure 2 illustrates the visual depiction of the procedural steps entailed in conducting the ARIMA estimation.

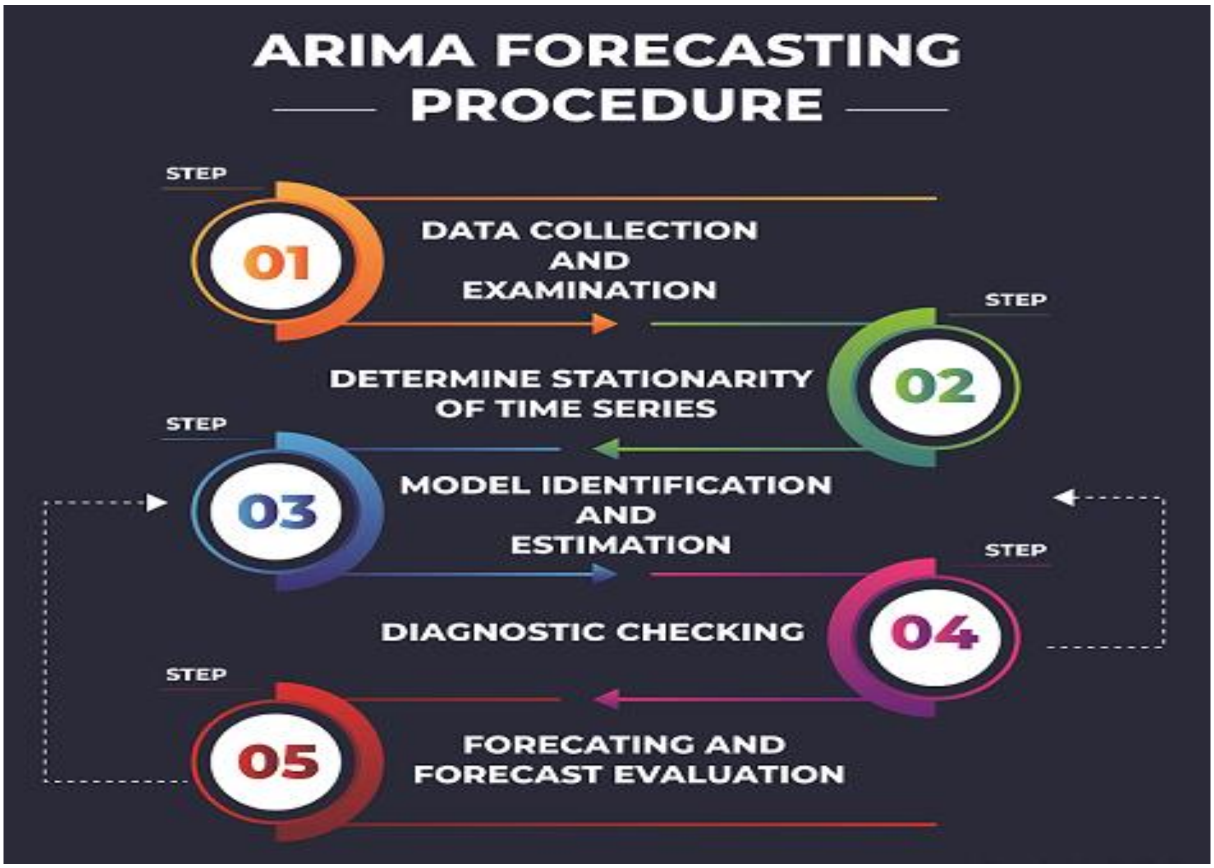


Fig. 2 ARIMA Forecasting Procedures

To ensure normal distribution and stabilize variance, each of the series underwent a log-transformation. This strategy is based on the prevailing notion that within any institution, human resources are essential and can offer a competitive edge. In the current fiercely competitive landscape, capable human resources stand as the most valuable asset for the education sector, particularly in the Higher Education industry. The formal econometric models expounded in this study are complemented in practical application by subjective 'off-model' inputs. Survey data from administrative staff at the University of Education, Winneba, was incorporated.

Consequently, forecasting using the Integrated Model of 360-degree Feedback leans more toward an art than a precise science, combining formal quantitative techniques with the insights and expertise of forecasters. The procedures for developing the ARIMA model for appraisal satisfaction, job performance, and job capability are outlined in the subsequent sub-sections.

ARIMA (p, d, q) Model for Job Performance

This study's job performance data spans the period from July 1, 2020, to December 12, 2021, with a total of 76 observations. Table 1 reveals that both the intercept and trend of the log of job performance are statistically significant ($p < 1\%$), hence should be specified accordingly in the ADF test.

Table 1: Regression of lnJP on its Intercepts and Trends

Variable in log	P-values Intercept	Trend
Job Performance	0.0001	0.0003

The ADF test as shown in Table 2 reveals that the log of job performance is stationary ($p < 1\%$) when both intercept and trend are specified in the test. This implies that the log of job performance is trend stationary and hence needs no further differencing. Thus, the log of appraisal satisfaction is integrated with order zero ie. $I(0)$ or D = 0.

Table 2: ADF test for the log of job performance at the level

p-values		
None	Intercept	Intercept and trend
0.8363	0.6705	0.0031

H_0: Series contain unit root H_1: Series is stationary

Table 3 shows the top 10 best ARIMA models for the log of job performance generated by Eviews based on the minimum Akaike Information Criterion (AIC). ARIMA (1,0,1) was chosen as the best model because firstly, it has the smallest AIC as shown in Table 3.

Table 3: Statistical Results of Different ARIMA Parameters for Job Performance

ARIMA Model	AIC
(1,0,1)	**-1.2697**
(1,0,2)	-1.2568
(2,0,1)	-1.2538
(3,0,0)	-1.2525
(2,0,0)	-1.2404
(4,0,0)	-1.2353
(3,0,1)	-1.2331
(1,0,3)	-1.2314
(2,0,2)	-1.2309
(3,0,3)	-1.2228

The ARIMA model is represented by bold rows above

Secondly, ARIMA (1,0,1) was chosen as the best model because all the parameters are statistically significant ($p < 1\%$) with a high R-squared of 0.7942 as shown in Table 4. The R-squared figure suggests that 79.42% of the variation in the log of job performance is explained by the ARIMA (1,0,1) model

Table 4: Results of ARIMA(1,0,1) for predicting log of Job Performance

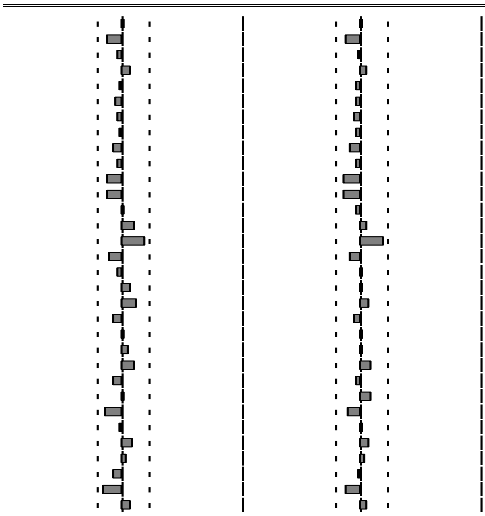
Dependent Variable: LNJP
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/01/22 Time: 16:10
Sample: 7/01/2020 12/08/2021

Included observations: 76
Convergence achieved after 7 iterations
Coefficient covariance computed using the outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.864565	0.167495	5.161730	0.0000
AR(1)	0.963595	0.034242	28.14049	0.0000
MA(1)	-0.369681	0.132402	-2.792117	0.0067
SIGMASQ	0.014438	0.002625	5.501107	0.0000

R-squared	0.802443	Mean dependent var	0.867142
Adjusted R-squared	0.794211	S.D. dependent var	0.272135
S.E. of regression	0.123451	Akaike info criterion	-1.269693
Sum squared resid	1.097289	Schwarz criterion	-1.147022
Log-likelihood	52.24832	Hannan-Quinn criteria.	-1.220668
F-statistic	97.48394	Durbin-Watson stat	1.924850
Prob(F-statistic)	0.000000		

Lastly, ARIMA (1,0,1) was chosen as the best model for forecasting the log of job performance because the residuals of this model are white noises as expected of good models. The residuals do not show any significant spikes of PACFs and ACFs, as shown in Figure 3, implying that the model does not suffer from serial correlation, hence good for prediction.



	AC	PAC	Q-Stat	Prob
1	0.011	0.011	0.0104	
2	-0.132	-0.132	1.3986	
3	-0.025	-0.022	1.4497	0.229
4	0.070	0.054	1.8524	0.396
5	-0.018	-0.026	1.8783	0.598
6	-0.057	-0.042	2.1495	0.708
7	-0.047	-0.050	2.3429	0.800
8	-0.022	-0.039	2.3860	0.881
9	-0.075	-0.089	2.8891	0.895
10	-0.033	-0.039	2.9889	0.935
11	-0.129	-0.153	4.4972	0.876
12	-0.116	-0.140	5.7473	0.836
13	0.018	-0.026	5.7781	0.888
14	0.109	0.060	6.9124	0.863
15	0.190	0.198	10.436	0.658
16	-0.109	-0.094	11.614	0.637
17	-0.027	-0.006	11.686	0.703
18	0.071	0.008	12.204	0.730
19	0.118	0.076	13.660	0.691
20	-0.068	-0.065	14.148	0.719
21	0.003	0.019	14.149	0.775
22	0.045	0.015	14.373	0.811
23	0.105	0.094	15.599	0.792
24	-0.081	-0.034	16.345	0.798
25	0.021	0.090	16.398	0.838
26	-0.152	-0.114	19.141	0.744
27	-0.015	0.012	19.166	0.789
28	0.098	0.068	20.351	0.775
29	0.040	0.026	20.552	0.807
30	-0.066	-0.019	21.109	0.821
31	-0.160	-0.126	24.501	0.704
32	0.069	0.046	25.137	0.718

Figure 3: Correlogram of residuals of lnJP

ARIMA (p, d, q) Model for Appraisal Satisfaction

The data for appraisal satisfaction used in this study covers the period from July 1, 2020, to December 12, 2021, with a total of 76 observations. Table 4 reveals that both the intercept and trend of the log of job performance are not statistically significant ($p > 5\%$), hence should not be included in the ADF test.

Table 5: Regression of lnAP on its Intercepts and Trends

Variable in log	**P-values** **Intercept**	**Trend**
Appraisal Satisfaction	0.0614	0.3356

As shown in the ADF test results in Table 5, the log of appraisal satisfaction is non-stationary at level ($p>5\%$). This implies that the mean and or the variance of the log of appraisal satisfaction changes over time.

However, the log of appraisal satisfaction became stationary after taking the first difference of the series (p < 5%). Therefore, the log of appraisal satisfaction is integrated into order 1 ie. $I(1)$ or $D = 1$

Table 6: ADF Test of Unit Root for lnAP

P-values of tests					
Level			First Difference		
None	Intercept	Intercept and trend	None	Intercept	Intercept and trend
0.4462	0.1913	0.3541	0.0001	0.0030	0.0165

H_0: Series contain unit root H_1: Series is stationary

Table 6 shows the top 10 best ARIMA models for the log of job performance generated by Eviews based on the minimum Akaike Information Criterion (AIC). ARIMA (0,1,3) was considered the best model for the log of appraisal satisfaction. The model returned the smallest AIC as shown in Table 6.

Table 7: Statistical Results of Different ARIMA Parameters For lnAS

ARIMA Model	AIC
(0,1,3)	**-3.373**
(1,1,4)	-3.3565
(0,1,4)	-3.3464
(1,1,3)	-3.3464
(2,1,3)	-3.3423
(2,1,4)	-3.3317
(3,1,4)	-3.3168
(3,1,3)	-3.3159
(2,1,1)	-3.3132
(4,1,3)	-3.3115

Among the various experiments, the bold row represents the best ARIMA model.

Further, as shown in Table 7, all the parameters are statistically significant (p < 1%). This suggests that the ARIMA (0,1,3) model for predicting the log of appraisal satisfaction has a relatively higher predictive capacity.

Dependent Variable: D(LNAS)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/02/22 Time: 09:44
Sample: 7/08/2020 12/08/2021
Included observations: 75
Convergence achieved after 27 iterations
Coefficient covariance computed using the outer product of gradients

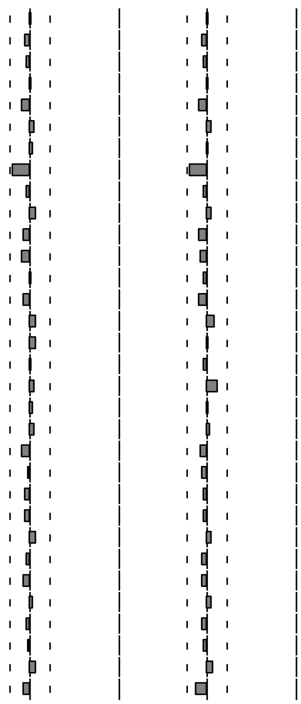
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001455	0.018166	0.080082	0.9364
MA(1)	0.795620	0.076487	10.40205	0.0000
MA(2)	0.461832	0.123758	3.731739	0.0004
MA(3)	0.534788	0.134837	3.966178	0.0002
SIGMASQ	0.001716	0.000205	8.378887	0.0000

R-squared	0.508201	Mean dependent var	0.001840
Adjusted R-squared	0.480098	S.D. dependent var	0.059461
S.E. of regression	0.042874	Akaike info criterion	-3.373035

Sum squared resid	0.128671	Schwarz criterion	-3.218536
Log-likelihood	131.4888	Hannan-Quinn criteria.	-3.311345
F-statistic	18.08364	Durbin-Watson stat	1.974262
Prob(F-statistic)	0.000000		

Figure 4: ARIMA (0,1,3) estimation output for lnAS

Lastly, the model does not suffer from serial correlation as there are no significant spikes of ACFs and PACFs as shown in Figure 5.



	AC	PAC	Q-Stat	Prob
1	0.009	0.009	0.0062	
2	-0.059	-0.059	0.2792	
3	-0.028	-0.027	0.3403	
4	0.002	-0.001	0.3405	0.560
5	-0.088	-0.091	0.9756	0.614
6	0.042	0.043	1.1212	0.772
7	0.035	0.023	1.2225	0.874
8	-0.199	-0.202	4.6194	0.464
9	-0.048	-0.038	4.8175	0.567
10	0.078	0.054	5.3620	0.616
11	-0.077	-0.097	5.9032	0.658
12	-0.083	-0.079	6.5304	0.686
13	0.010	-0.030	6.5397	0.768
14	-0.068	-0.085	6.9720	0.801
15	0.070	0.093	7.4372	0.827
16	0.072	0.005	7.9395	0.848
17	0.002	-0.037	7.9400	0.892
18	0.064	0.121	8.3592	0.909
19	0.031	-0.003	8.4611	0.934
20	0.055	0.038	8.7779	0.947
21	-0.094	-0.078	9.7180	0.941
22	-0.024	-0.062	9.7828	0.958
23	-0.062	-0.039	10.209	0.964
24	-0.057	-0.049	10.576	0.970
25	0.081	0.049	11.329	0.970
26	-0.043	-0.049	11.546	0.977
27	-0.075	-0.050	12.218	0.977
28	0.025	0.044	12.297	0.984
29	-0.034	-0.063	12.444	0.988
30	-0.024	-0.026	12.517	0.992
31	0.076	0.069	13.269	0.992
32	-0.079	-0.138	14.103	0.991

Fig. 5: Correlogram of residuals of lnAS

ARIMA (p, d, q) Model for Job Capability

The research utilizes job capability data spanning from July 1, 2020, to December 12, 2021, encompassing a total of 76 observations. As depicted in Table 7, it becomes evident that both the intercept and the trend associated with the logarithm of job capability hold statistical significance ($p < 1\%$). Consequently, these significant factors should be accurately specified within the Augmented Dickey-Fuller (ADF) test.

Table 8: Regression of lnJC on its Intercepts and Trend

Variables in log	P-values	
	Intercept	**Trend**
Job Capability	0.0002	0.0023

The ADF test as shown in Table 8 reveals that the log of job performance is stationary ($p < 1\%$) when both intercept and trend are specified in the test.

Table 9: ADF test for lnJC

Variables in log	None	Intercept	Intercept and Trend
Job Capability	0.9126	0.1726	0.0071

H_0: Series contain unit root H_1: Series is stationary

Table 9 displays the top 10 most favorable ARIMA models for the logarithm of job capability as generated by Eviews, using the minimum Akaike Information Criterion (AIC) as the basis. The ARIMA(4,0,3) model emerges as the one with the minimum AIC for the logarithm of job capability (lnJC). However, this model didn't pass the significance test for parameters, as all the Moving Average (MA) parameters were statistically insignificant at the 5% significance level. Consequently, the ARIMA model with the second smallest AIC, namely ARIMA (4,0,2), was taken into consideration. Unfortunately, this model also didn't pass the parameter significance test, as one of the MA parameters was statistically insignificant at the 5% significance level. Subsequently, the ARIMA model with the next smallest AIC, i.e., ARIMA(4,0,0), was considered.

Table 10: **Statistical Results of Different ARIMA Parameters For lnJC**

ARIMA Model	AIC
(4,0,3)	-2.8000
(4,0,2)	-2.7769
(4,0,0)	**-2.7711**
(4,0,1)	-2.7543
(1,0,1)	-2.7502
(3,0,3)	-2.7424
(1,0,2)	-2.731
(2,0,4)	-2.7291
(2,0,1)	-2.7289
(1,0,3)	-2.7131

The bold row represents the best ARIMA model among the several experiments

ARIMA (4,0,0) model passed the parameter significance test as all the parameters were statistically significant at the 1% significance level with a high R squared of 0.9127 as shown in Figure 5. The R squared revealed that 91.27% of the variations in the log of job capability are explained by the model.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.772815	0.080116	9.646227	0.0000
AR(1)	1.564343	0.091918	17.01898	0.0000
AR(2)	-1.045745	0.183432	-5.701000	0.0000
AR(3)	0.724566	0.176807	4.098060	0.0001
AR(4)	-0.329715	0.094071	-3.504944	0.0008
SIGMASQ	0.002997	0.000455	6.580532	0.0000

R-squared	0.918558	Mean dependent var	0.749130
Adjusted R-squared	0.912741	S.D. dependent var	0.193098
S.E. of regression	0.057040	Akaike info criterion	-2.771095
Sum squared resid	0.227752	Schwarz criterion	-2.587090
Log-likelihood	111.3016	Hannan-Quinn criteria.	-2.697558
F-statistic	157.9021	Durbin-Watson stat	2.004962
Prob(F-statistic)	0.000000		

Figure 6: ARIMA (4,0,0) estimation output for lnJC

Finally, the residuals of the chosen model are white noises. Figure 6 shows that there are no significant ACF or PACF spikes in the residuals, indicating that the model is good.

	AC	PAC	Q-Stat	Prob
1	-0.022	-0.022	0.0398	
2	0.058	0.058	0.3133	
3	-0.025	-0.022	0.3624	
4	0.075	0.071	0.8293	
5	0.046	0.052	1.0067	0.316
6	-0.043	-0.051	1.1651	0.558
7	-0.068	-0.073	1.5607	0.668
8	0.088	0.089	2.2377	0.692
9	-0.079	-0.078	2.7839	0.733
10	-0.191	-0.210	6.0614	0.416
11	-0.046	-0.026	6.2522	0.511
12	0.110	0.134	7.3634	0.498
13	0.148	0.155	9.4305	0.399
14	-0.114	-0.099	10.683	0.383
15	-0.021	-0.019	10.725	0.467
16	0.061	0.048	11.090	0.521
17	0.198	0.176	15.010	0.307
18	-0.036	-0.013	15.143	0.368
19	0.234	0.241	20.861	0.141
20	0.005	-0.032	20.865	0.184
21	0.136	0.042	22.862	0.154
22	-0.085	-0.010	23.654	0.167
23	-0.071	-0.033	24.214	0.188
24	0.001	-0.067	24.214	0.233
25	0.050	-0.015	24.508	0.269
26	0.061	0.174	24.955	0.299
27	-0.095	-0.022	26.053	0.298
28	-0.065	-0.064	26.575	0.325
29	-0.039	-0.054	26.766	0.368
30	0.026	0.035	26.851	0.417
31	-0.028	-0.014	26.954	0.466
32	0.042	-0.024	27.193	0.508

Fig. 7: Correlogram of residuals of lnJC

Validation of Questionnaire

The constructs within the questionnaire underwent validation to confirm their alignment with their intended measurements. Cronbach's Alpha and the Kaiser-Meyer-Olkin (KMO) statistics were employed for the validation process. The Kaiser-Meyer-Olkin (KMO) test was used to ensure the sufficiency of the sampling.

The outcomes are presented in Table 10. According to Kaiser (1974), a minimum threshold of 0.5 is suggested. In this context, the KMO value of 0.706 surpasses this threshold, signifying that the items within the questionnaire offer an ample sample size.

Table 11: Kaiser-Meyer-Olkin Measure of Sampling Adequacy

KMO	0.706

The assessment of internal consistency for each construct was carried out using the Cronbach's Alpha coefficient, which measures the extent to which a set of items evaluates a specific construct. Ursachi et al. (2015) advocate a well-accepted standard, where a Cronbach's Alpha value falling between 0.6 to 0.7 indicates an acceptable level of reliability, while a value of 0.8 or higher suggests a highly reliable level. The results of Cronbach's Alpha, as depicted in Table 11, demonstrate that all constructs attain either an acceptable or a highly reliable level of internal consistency.

Table 12: Cronbach Alpha Test for Internal Reliability

	Job Performance	Appraisal Satisfaction	Job Capability
The number of items on the scale:	06	03	03
Scale reliability coefficient:	0.83	0.76	0.79

Descriptive Statistics

Table 12 provides descriptive statistics regarding job capability, job performance, and appraisal satisfaction. The mean score for job capability fluctuated between a minimum of 1.472 on September 1, 2020, and a maximum of 3.412 on August 1, 2021, with an overall mean of 2.155 and a standard deviation of 0.435. The mean score for job performance is 2.469, accompanied by a standard deviation of 0.679. This metric ranged from a minimum of 1.460 on October 1, 2020, to a peak of 4.460 on August 1, 2021. Appraisal satisfaction exhibited an average score of 2.277, featuring a standard deviation of 0.562. The range spanned from a low of 1.420 on October 3, 2021, to a high of 3.677 on August 1, 2021.

Table 13: Descriptive Statistics on Research Variables

	Job Capability	Job Performance	Appraisal Satisfaction
Mean	2.155	2.469	2.277
Std. Dev.	0.435	0.679	0.562
Maximum	3.412	4.460	3.677
Minimum	1.472	1.460	1.420
Observations	76	76	76

Drawbacks of the Existing Performance Appraisal Model

Integrated Model of 360-Degree Feedback for Administrative Staff in Ghana's HEIs

As highlighted by Hosain (2015), an institution's overall performance and productivity aren't exclusively determined by the most advanced technology, the perfect business strategy, or even the magnitude of financial resources at hand. The paramount influence stems from how effectively institutions leverage their motivated, committed, skilled, and effective employees. The accomplishment and effectiveness of institutions are fundamentally molded by their ability to tap into the potential of their workforce.

For organizations to maintain competitiveness and longevity in any industry, it is imperative that they facilitate their employees in adapting, evolving, and proficiently fulfilling their roles and obligations. Consequently, prior to implementing any alterations, organizations must comprehensively assess the performance of their human resources and ascertain if any adjustments are necessary. This strategic approach ensures that employees remain equipped to meet evolving demands and challenges.

The majority of Higher Education Institutions typically assign an appraiser who assesses subordinates and compiles reports for various objectives, including promotion evaluations (Kodi and Sharath Kumar, 2020). As organizations increasingly adopted flatter organizational structures and faced heightened demand, many private and profit-driven institutions embraced the 360-degree feedback appraisal method. This approach was adopted to equip employees with the necessary insights to navigate substantial transformations and align their competencies and potential with the overarching goals of the organization.

When compared to single-rated feedback techniques, 360-degree feedback offers several notable advantages. Multi-rated feedback, which aggregates input from various individuals instead of relying solely on a single person's perspective, encompasses multiple viewpoints and perspectives, thereby offering a more comprehensive assessment of an employee's performance. As outlined by Maylett (2009), supervisors might not always be available to closely observe or evaluate their subordinates' performance, making it crucial to involve colleagues, customers, or students, particularly in the context of Higher Education Institutions (HEIs). By collectively contributing, subordinates, colleagues, customers, and supervisors provide a more holistic overview of an employee's conduct and productivity. In this collaborative approach, managers are better poised to gather candid feedback from a range of stakeholders, including clients, students, and appraisee colleagues. This collective input can lead to a more impartial appraisal judgment for the purpose of staff performance management.

Enhancing the assessment process or procedure by strategically making such inputs more evaluative and connecting it directly to the manager's evaluation is the second justification for the implementation of 360-degree feedback. Businesses seek to maximize their efforts, thus there are pressures to provide 360-degree evaluation input, according to a recent experience.

Kouzes and Posner (1993) emphasize that the utilization of 360-degree feedback stands out as one of the most potent and efficient approaches for evaluating employee productivity. Building upon this, Basu (2015) underscores the necessity for legitimacy, dependability, and accountability throughout the entire process of 360-degree feedback appraisals. This entails interventions aimed at heightening awareness regarding the importance of aligning actions with customer expectations, work unit performance, and leadership development.

These scholars acknowledge the vital role of soliciting employee feedback from diverse sources. Moreover, they recognize the challenges management encounters when conducting performance reviews. Through a case study of the University of Education, Winneba in Ghana, the researcher constructed an Integrated Model of 360-Degree Feedback performance appraisal (depicted in figure 7). This model is designed to elevate the productivity of administrative staff within Higher Education Institutions (HEIs) and enhance the quality of academic services. This enhancement is achieved by integrating the principles of the 360-degree feedback appraisal method into the model's framework.

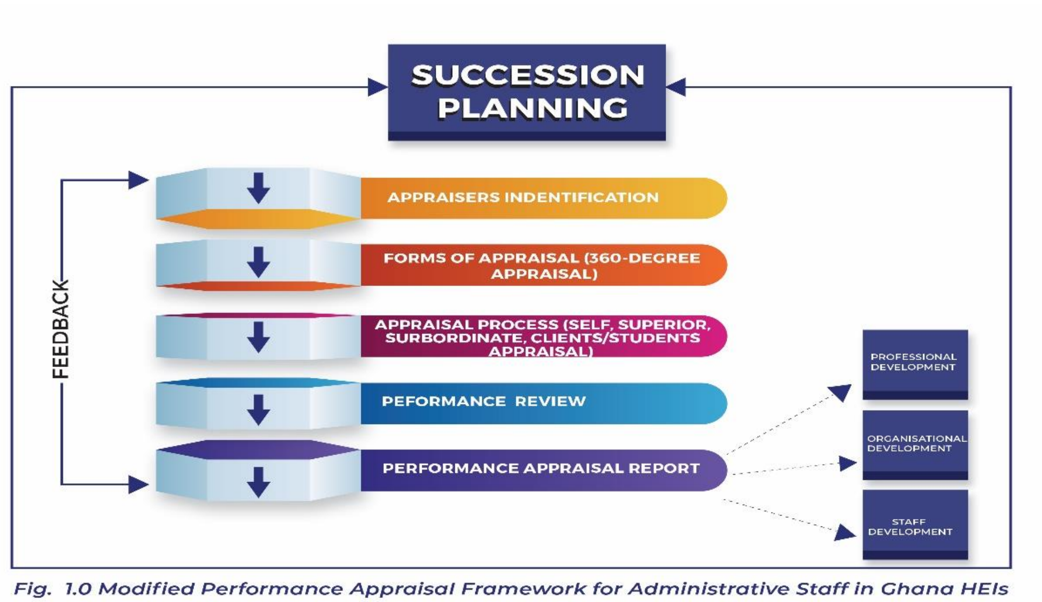


Fig. 8: An Integrated Model of 360-Degree Feedback

Results and Discussions

The results of job performance, job capability and appraisal satisfaction are presented and discussed in this session.

Results of ARIMA Model for Job Performance Prediction

Table 14 presents the outcomes of the job performance prediction model employing ARIMA (1,0,1). The Root Mean Square Error (RMSE) value of 0.12 indicates a well-fitted model. Figure 8 graphically illustrates the forecasted job performance compared to the actual values. Notably, the graph demonstrates a strong alignment between predicted and actual values, indicating the model's high predictive accuracy in forecasting job performance.

Table 14: Sample of Empirical Results for Arima (1,0,1) of log of job performance

Date	Actual	Predicted	log Inverse for predicted (Likert scale)
7/1/2020	0.471877	0.633075	1.883393
7/8/2020	0.607045	0.510635	1.66635
7/15/2020	0.580538	0.584416	1.793943
7/22/2020	0.604862	0.592292	1.808128

7/29/2020	0.410784	0.609679	1.83984
8/5/2020	0.440832	0.500813	1.650062
8/12/2020	0.469378	0.478431	1.613541
8/19/2020	0.497132	0.487112	1.627609
8/26/2020	0.673455	0.506804	1.659978
9/2/2020	0.522952	0.618805	1.856707
RMSE =0.12			

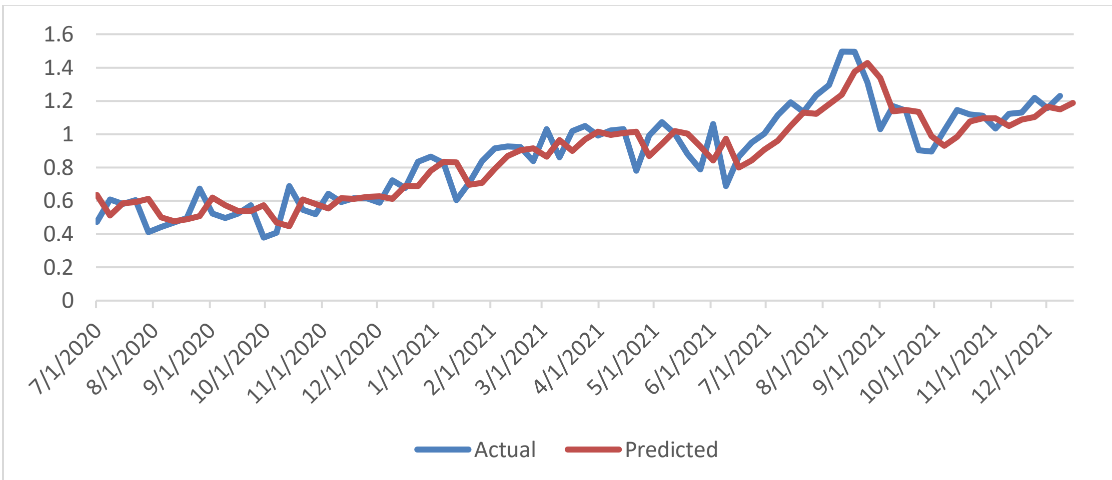


Figure 8: Graph of Actual job performance vs Predicted Job Performance

Results of the ARIMA Model for Appraisal Satisfaction Prediction

Table 14 displays a comparison between the actual and predicted Appraisal Satisfaction scores, employing ARIMA (0,1,3). Figure 7 visually represents this data graphically in Figure 9. As evidenced by the information in Table 14 and the graph in Figure 9, the predicted Appraisal Satisfaction scores closely mirror the actual values. This alignment is substantiated by the notably low Root Mean Square Error (RMSE) of 0.04. The graph's pattern of closely overlapping predicted and actual values further underscores the commendable performance of the chosen ARIMA model.

Table 14: Sample of Empirical Results for ARIMA (0,1,3) of log of Appraisal Satisfaction

Date	Actual	Predicted	log Inverse for predicted (Likert scale)
7/8/2020	0.0190	0.0015	1.0015
7/15/2020	0.0554	0.0131	2.0146
7/22/2020	0.1233	0.0378	2.0517
7/29/2020	0.0815	0.0833	2.1254
8/5/2020	0.0286	0.0562	2.1447
8/12/2020	-0.0336	0.0184	2.0764
8/19/2020	-0.0869	-0.0512	1.9687
8/26/2020	-0.0952	-0.0627	1.8893
9/2/2020	-0.0177	-0.0659	1.8754
RMSE = 0.04			

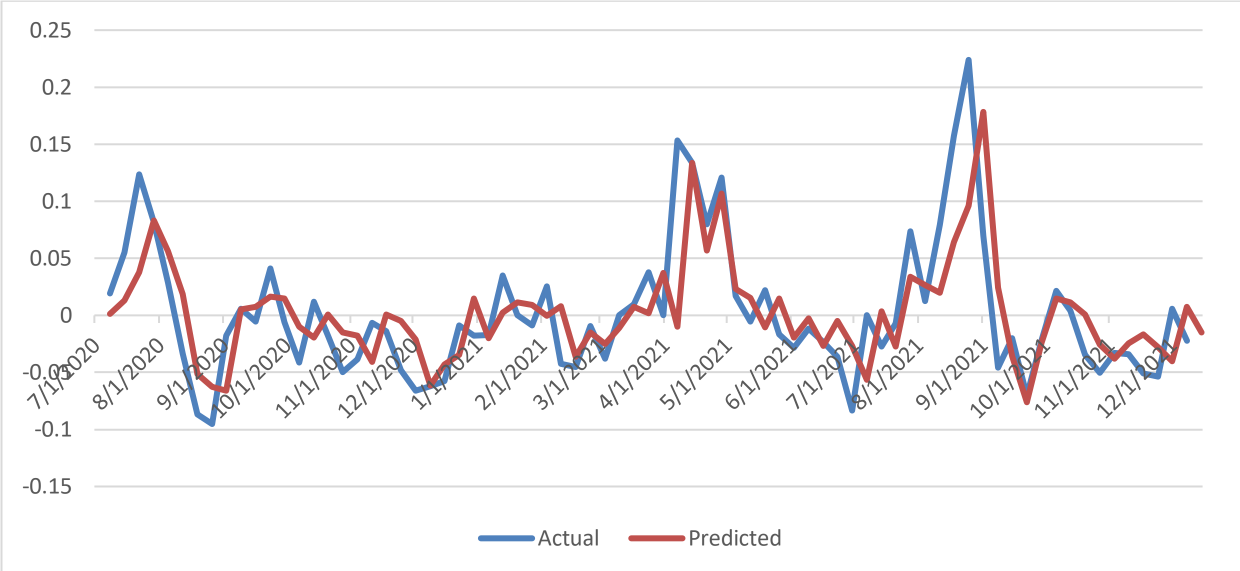


Figure 9: Graph of Actual job performance vs Predicted Appraisal Satisfaction

Results of the ARIMA Model for Job Capability Prediction

The results of the ARIMA (4,0,0) model for job capability prediction are shown in Table 15. Figure 10 graphically represents the model prediction performance. It can be observed that the predicted values follow closely to the actual values indicating a good model fit. The small RSME of 0.05 further confirms that the model is fit for prediction.

Table 15: Sample of Empirical Results for ARIMA (4,0,0) of log of Job Capability

Date	Actual	Predicted	log Inverse for predicted (Likert scale)
7/29/2020	0.426339	0.464893	1.591843
8/5/2020	0.392933	0.435821	1.546232
8/12/2020	0.386622	0.394011	1.482917
8/19/2020	0.473478	0.417566	1.518262
8/26/2020	0.480034	0.547396	1.728746
9/2/2020	0.497184	0.473266	1.605228
9/9/2020	0.524027	0.558252	1.747615
9/16/2020	0.532452	0.558422	1.747911
9/23/2020	0.537183	0.553795	1.739844
9/30/2020	0.53682	0.56618	1.761525
RMSE = 0.05			

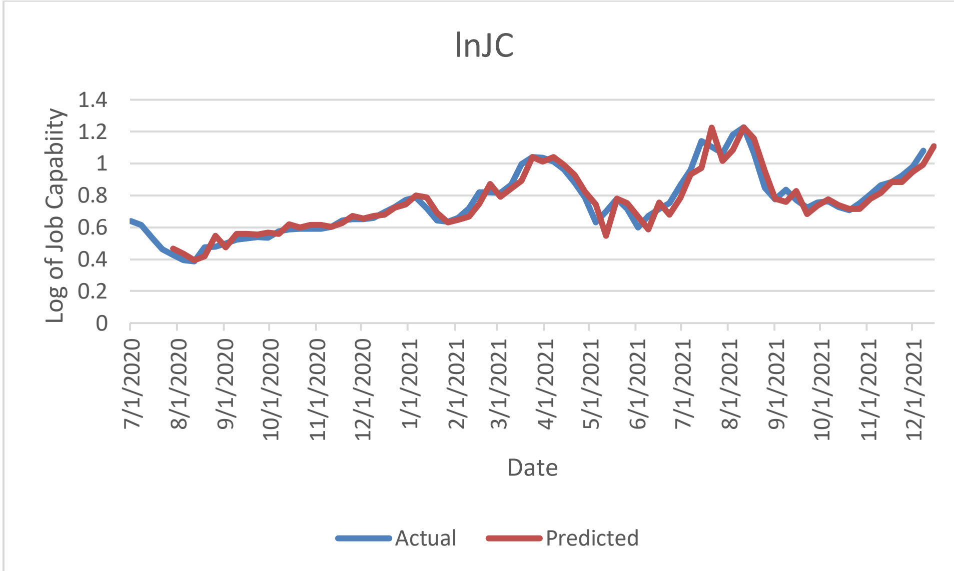


Figure 10: Graph of Actual job performance vs Predicted log of job capability

Conclusion

The Integrated Model of 360-Degree Feedback for HEIs in Ghana was evaluated to determine its efficacy for effective Performance Appraisal on Administrative Staff of HEIs in the Ghanaian Context. Eviews (Statistical Software) was used to forecast time series using the ARIMA Model to make scientific predictions based on historical time-stamped data. The Integrated Model of 360-Degree Feedback historical analyses were examined over time to help make observations and drive future strategic decision-making about the model's effectiveness.

The paper emphasizes the importance of 360-degree feedback in evaluating employee performance, especially in higher education institutions (HEIs) in Ghana. This approach gathers input from various sources, providing a more comprehensive view of an employee's performance compared to traditional single-rated feedback.

The paper highlights that effective employee development and performance enhancement are crucial for organizational effectiveness and competitiveness. It suggests that institutions should focus on harnessing the potential of their employees through proper feedback mechanisms and performance evaluation processes.

The paper demonstrates that the ARIMA models used for predicting job performance, appraisal satisfaction, and job capability show a high degree of accuracy over the short term. This suggests that the integrated model could be a valuable tool for enhancing performance appraisal and decision-making processes in HEIs.

The theoretical contributions of this thesis can be stated as follows; (1) By developing an Integrated Model of 360-Degree Feedback using the 360 Degree Feedback appraisal method, this research work empirically investigated and established the autocorrelations in the data between appraisal satisfaction and job capability in predicting the likelihood of high job performance.

(2) This paper details the thorough process of developing an ARIMA model for forecasting job capability, appraisal satisfaction, and job performance. The findings showed that ARIMA models can predict job performance, appraisal satisfaction, and job capability with high accuracy over the short term.

The paper presents results from a specific case study, and it would be beneficial to validate the proposed integrated model in different HEIs in Ghana and potentially in other countries. This external validation would enhance the generalizability of the findings. Again, The integrated model presented in the paper focuses on three dimensions (appraisal satisfaction, job capability, and job performance). Future research could explore more comprehensive multidimensional models that consider additional factors contributing to employee performance.

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Sincerely,

Richard Kodi

References

Ariyachandra, T. R., & Frolick, M. N. (2008). Critical success factors in business performance management—Striving for success. *Information systems management*, *25*(2), 113-120.

Basu, T. (2015). “Integrating 360 degree feedback in performance appraisal tool and development process”. IOSR Journal of Business and Management, Vol. 17, No.1, pp. 50-61. DOI: 10.9790/487X-17135061

Baroda, S., Sharma, C. and Bhatt, J. K. (2012). “360 Degree Feedback Appraisals- An innovative approach of Performance Management System”. *International Journal of Management & Information Technology*, Vol. 1, No. 2, pp. 53-66.

Fwaga, S.O., Orwa G., and Athiany, H., (2017). Modelling rates of inflation in Kenya: an application of GARCH and EGARCH models, Mathematical Theory and Modeling, 7 (5): 75 – 83.

Hamidi, H., & Sarfarazi, M. (2010). Globalization and human resources management. *Strategic Studies of public policy*, *1*(1), 1-48.

Hosain, M. S. (2015). “Adoption of Proper HRM Practices: A Technique for Retaining Employees and Increasing Firm Performance?” *Scholar Journal of Business and Social Science*, Vol. 1, No. 1, pp. 1-14.

Jabeen, M. (2011). Impact of Performance Appraisal on Employees Motivation. *European Journal of Business and Management*, *3*(4), 197-204.

Kouzes, J. H. & Pozner, B. Z. (1993). "Credibility – How Leaders Gain and Lose It, Why People Demand It". San Francisco: Jossey – Bass publishers, pp. 97-98.

Lidiema, C., (2017). Modeling and forecasting inflation rate in Kenya using SARIMA and Holt–Winters Triple Smoothing, Science Publishing Group – *American Journal of Theoretical and Applied Statistics*, 6 (3): 161 – 169.

Maylett, T. (2009). "360-degree feedback revisited: The transition from development to appraisal”. *Decision-wise Leadership Intelligence*, pp. 1-8. Retrieved from www.decwise.com.

Muthiani, B. (2021). *The Relationship Between Performance Appraisal System, Employee Motivation and Labor Productivity: a Study of Pesapal Organization* (Doctoral dissertation, University of Nairobi).

Neely, A., Marr, B., Roos, G., Pike, S., & Gupta, O. (2003). Towards the third generation of performance measurement. *Controlling*, *15*(3/4), 129-135

Sideratos, G., & Hatziargyriou, N. D. (2007). An advanced statistical method for wind power forecasting. *IEEE Transactions on power systems*, *22*(1), 258-265.

Uwilingiyimana, C., Mungatu J., and Harerimana, J.D., (2015). Forecasting inflation in Kenya using ARIMA – GARCH models, *International Journal of Management and Commerce Innovations,* 3 (2): 15 – 27.

Vithana, K., Jayasekera, R., Choudhry, T., & Baruch, Y. (2021). Human Capital resource as cost or investment: A market-based analysis. *The International Journal of Human Resource Management*, 1-33.

Van Thiel, S., & Leeuw, F. L. (2002). The performance paradox in the public sector. *Public Performance & management review*, *25*(3), 267-281.

Wong, W. P., & Wong, K. Y. (2008). A review on benchmarking of supply chain performance measures. *Benchmarking: An international journal*.