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Unlocking Workforce Insights: Exploratory Data Analysis for Strategic Workforce Planning in State Universities and Colleges (SUCs)

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ABSTRACT
Workforce decisions should be supported by workforce data analytics rather than relying solely on intuition. This can now be addressed with the use of IT-based techniques such as workforce analytics, which helps to transform raw data into insightful and quantifiable results. Relative to this, this paper looks into exploratory data analysis (EDA) to gain significant insights. The study employs a quantitative approach using sample data from an SUC in the Bicol Region, Philippines. EDA is conducted within the Jupyter Notebook employing descriptive statistics, Latent Dirichlet Allocation (LDA), Jaccard Similarity, and Auto-Regressive Integrated Moving Average (ARIMA) for predictive modeling. The results of the analysis reveal insights across various dimensions such as distributions across age, gender, civil status, employment status, educational levels, length of service, and even positions that will be vacated in the succeeding years. Notably, the LDA approach uncovers the skills and expertise of the current workforce, highlighting dominant expertise such as Information Technology and Nursing within the administrative and academic cluster, respectively. Jaccard similarity result suggests that there is a certain level of alignment and gap between the expertise possessed by the current workforce with the expertise required by the Commission on Higher Education (CHED). Forecasts derived through ARIMA modeling project a student enrollment for the next semester, with corresponding prediction accuracy metrics such as Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error. Finally, the analysis concludes with projecting for faculty workforce demand to accommodate future student enrolment, thus offering a strategic approach to workforce planning.

Keywords: Auto-Regressive Integrated Moving Average (ARIMA), exploratory data analysis, Jaccard Similarity, strategic workforce planning, SUCs, Latent Dirichlet Allocation (LDA)

INTRODUCTION

The workforce is the most important asset of any organization [14]. With this important asset, workforce management is always a challenge[19]. In the present context, workforce decisions should be supported by workforce data and analytics rather than relying solely on intuition and instincts[14]. The challenge of workforce management can now be addressed with the use of new IT-based techniques such as HR or Workforce analytics, which helps to transform raw data into insightful and quantifiable results. Through HR or workforce analytics, workforce planning can be made in a more strategic approach. In the study of Momin and Mishra[2015] entitled " HR Analytics as a Strategic Workforce Planning", workforce analytics is defined "as an evidence-based approach that contains the elements of business intelligence, tools and methods ranging from simple reporting of HR metrics to predictive model and its purpose is to enable the organizations to make better strategic decisions on the people side of the business" [p.258]. Through identifying patterns, trends, and correlations in the workforce data, the significance brought by workforce analytics as mentioned by Tuli et.al [30] includes understanding the workforce pool, identifying areas for improvement, and making data-driven decisions to improve performance and productivity as well as evaluate human resource activities, discover workforce retention factors and match human resource strategies with the organizations' goal.

In an era characterized by rapid technological advancements, evolving educational landscapes, and dynamic workforce demands, the effective alignment of the workforce with organizational objectives has become paramount for the success of educational institutions. State Universities and Colleges (SUCs) in the Philippines, as pillars of academic excellence and drivers of societal progress, are tasked with the challenge of navigating these complexities while ensuring optimal utilization of their workforce resources. Data-driven approaches have emerged as a transformative tool in workforce planning, allowing organizations or institutions to use insights from massive datasets to influence strategic decision-making and resource allocation. One good instance is the study of Chianan and Nhu [2013]entitled "Forecasting the Manpower Requirement in Vietnamese Tertiary Institutions". The study analyses and gets prediction values of students and faculty members in all Vietnamese universities for the future by taking the data provided by the Ministry of Vietnamese Education. However, though many institutions are investing in data science and analytics, most fail to be truly data-driven, this is being asserted by Google's Chief Decision Scientist Cassie Kozyrkov at the Open Data Science Conference[8].

Exploratory data analysis (EDA) is particularly important in data-driven decision-making, as it provides a systematic framework for revealing hidden patterns, trends, and linkages within workforce data. According to Hussain and Athal [2023], "data need to be analyzed to produce good results…using the result, a decision can be generated"[p.11]. This is true with the implementation of exploratory data analysis for workforce planning.

Despite the potential benefits of workforce analytics, published literature on the actual implementation of exploratory data analysis particularly in the context of tertiary education institutions remains limited.

In relation to the aforementioned insights and facts, this study, titled "Unlocking Workforce Insights: Exploratory Data Analysis for Workforce Planning," attempts to investigate the use of EDA techniques in the context of workforce planning within SUCs. By exploring into collection of workforce data available in the sample SUC, this study aims to uncover useful insights that can inform proactive workforce planning, succession planning, and organizational development plans. Specifically this study seeks to uncover the following insights through exploratory data analysis of workforce data: demographic diversity, skills, and expertise of the current workforce, faculty-staff ratio, faculty-student ratio, and succession need; to identify key skills gaps and expertise demand; and to apply predictive modeling technique to forecast future workforce demand through student enrolment.

The significance of this research lies in its potential to empower SUCs with the knowledge and tools needed to navigate the complexities of the modern workforce landscape. By employing the power of data analytics, institutions can gain a deeper understanding of their workforce dynamics, anticipate future staffing needs, and cultivate a culture of data-driven decision-making.

Through a comprehensive exploration of workforce data, this paper aims to contribute to the broader discourse on effective workforce planning strategies in educational institutions. By unlocking the insights hidden within their data, SUCs can position themselves as flexible, forward-thinking organizations capable of meeting the challenges of the future head-on.

2) METHODS AND METHODOLOGY

The methodology employed in this study aimed to uncover valuable insights into workforce planning through exploratory data analysis (EDA) and predictive modeling techniques.

This study adopts the EDA steps stipulated in the book Hands-on Exploratory Data Analysis with Python[28] illustrated in the following figure.

Figure 1 Exploratory Data Analysis Steps

As shown in Figure 1, the EDA steps employed are as follows:

1. Problem Definition. In this step, the researcher clearly defines the objective of the analysis. The objective of the analysis in this study is to uncover insights from the sample workforce data such as demographic diversity; skills and expertise of the current workforce; the faculty-staff and faculty-student ratio; the succession need; and key skills gaps and expertise demand. Further, it aims to use predictive modeling techniques to forecast future workforce demand based on student enrolment.

2. Data Collection and Preparation. Workforce data from a sample SUC in the Bicol Region was collected for analysis. The data were obtained primarily from the Human Resource and Development Office, Dean's Office, and the Registrar's Office of the sample SUC. The dataset included information on demographic attributes, educational level, employment status, and length of service for both administrative and academic staff as well as the enrolment data. The dataset was preprocessed to handle missing values, standardize data formats, and ensure consistency across variables.
3. Data Analysis. For this step, EDA was conducted to gain a comprehensive understanding of the workforce composition and characteristics. EDA was implemented using Python programming language and in the Jupyter Notebook platform. Descriptive statistics including mean, standard deviation, frequency, and percentage were computed to summarize numerical variables such as age, length of service, gender, civil status, status of employment, and educational level. Visualizations such as histograms, bar charts, pie graphs, heat maps, and violin plots were utilized to explore patterns and relationships within the data. Topic modeling using Latent Dirichlet Allocation (LDA) was employed to identify clusters of skills and expertise among staff members. The Jaccard similarity index was also used to assess the skills gap based on the current workforce dataset. To forecast the future workforce demand based on the enrolment projections, predictive modeling techniques including Autoregressive Integrated Moving Average (ARIMA) were applied. The ARIMA model was trained on historical enrollment data (10 semesters) and used to predict enrollment numbers for upcoming semesters. Prediction accuracy metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared (RMSE) were computed to evaluate the performance of the predictive model.
4. Development and Representation of the Results. In this step, the results from the EDA and predictive modeling were presented and interpreted. Implications of the findings were discussed also in the context of strategic workforce planning and resource allocation within the SUC.

3] RESULTS AND DISCUSSION:

This section presents the results of the exploration into workforce insights, utilizing comprehensive data analysis techniques to unveil key trends, patterns, and implications. Through a combination of descriptive statistics, exploratory data analysis, and predictive modeling, the results presented in this section concentrate on the demographic composition, skill landscape, and future projections of the workforce within the sample State University and College. This section aims to interpret and contextualize the findings, shedding light on their significance for workforce planning and strategic decision-making.

a. Demographic Diversity

Insightful understanding of the workforce demographics is the heart of strategic workforce planning [4]. Because of that, this subsection presents the demographic composition of the workforce, highlighting key insights such as age distribution, gender diversity, civil status, educational levels, and length of service. Interpretation and implications of these demographics on workforce dynamics and organizational needs are given emphasis.

Age Distribution

Understanding the age composition of the workforce is essential for gauging the demographic landscape and anticipating future workforce dynamics[2,20]. On the workforce dataset set used for exploratory data analysis, the violin plot shown in Fig. 2 visualizes the age distribution of the workforce.

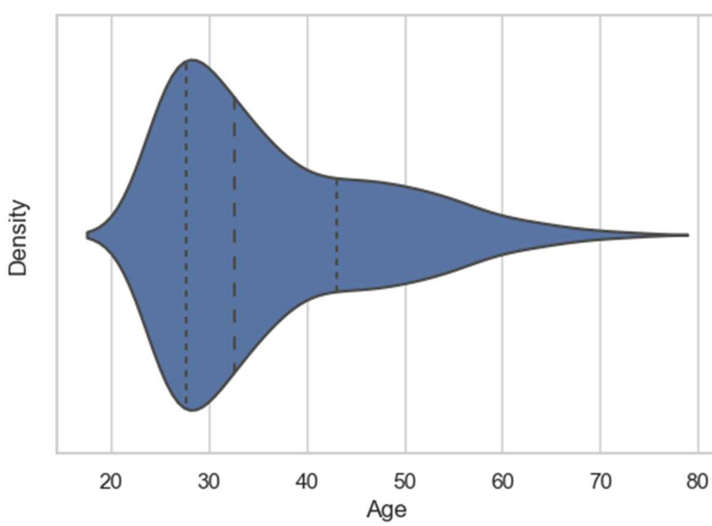


Figure 1 Violin Plot of Age Distribution

The age distribution suggests that the workforce spans a wide range of ages, with a central tendency around the late 30s which is in the mid-career stage. These employees likely have a combination of experience and energy, making them valuable contributors to the organization. This diversity in age can bring a variety of perspectives, experiences, and skills to the organization, supporting innovation, knowledge sharing, and organizational resilience. In fact as cited in the study entitled "Diversity Improves Performance and Outcomes", age diversity is associated with improved operation and organizational performance[12,17]. This also underscores the importance of implementing age-inclusive policies and practices to support the diverse needs of employees across different life stages.

Gender Distribution

In today's evolving workplace landscape, achieving gender balance is not just a matter of compliance with regulatory requirements but a strategic imperative for organizations seeking to thrive in a competitive environment[31]. Research consistently demonstrates that gender-diverse teams are more innovative, productive, and better equipped to meet the diverse needs of customers and stakeholders.

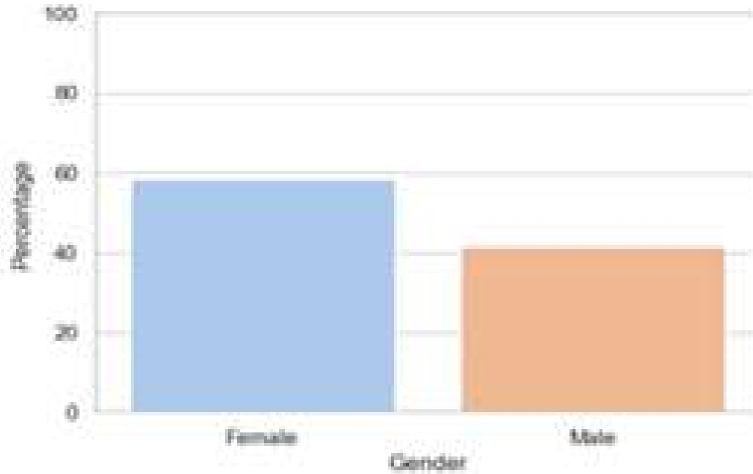


Figure 3 Gender Distribution

In analyzing the workforce demographics of the sample dataset, a notable finding emerged regarding gender distribution as shown in Figure 3. The data revealed a total of 465 (59%) female employees and 330 (41%) male employees within the organization. This suggests that there is a gender imbalance within the workforce, with a higher representation of female employees compared to male employees. Understanding gender distribution is important for ensuring gender equality and diversity in the workplace. It also provides valuable insights for designing inclusive policies and initiatives to promote gender balance, equal opportunities, and a supportive work environment for all employees, regardless of gender. Relevant to this, a report entitled "Delivering Through Diversity" affirms the correlation between diversity and financial performance in organizations, emphasizing the importance of gender diversity in driving business performance [31].

Civil Status Distribution

The civil status distribution among employees reveals important insights into the personal demographics and life circumstances of the workforce. Figure 4 presents the civil status distribution of the sample dataset.

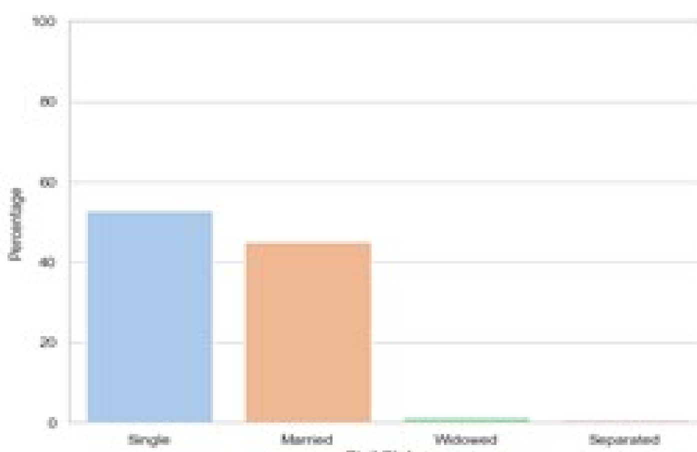


Figure 4 Civil Status Distribution

Among the findings, the data shows that a majority of employees are single, comprising 405 (52%) individuals. This indicates that a significant portion of the workforce may be at a stage in their lives where they prioritize individual pursuits and professional development. Moreover, the presence of 346 (45%) married employees suggests that a substantial number of individuals within the workforce are likely to have additional responsibilities and commitments outside of work, such as family obligations and caregiving responsibilities. Understanding the needs and challenges faced by married employees can inform organizational policies and practices aimed at promoting work-life balance and supporting employee well-being. The smaller proportions of widowed and separated employees, comprising 11(2%) and 5 (1%) individuals respectively, highlight the importance of recognizing and accommodating employees who may be navigating significant life transitions or experiencing personal loss. Sensitivity to the unique needs and circumstances of these individuals can contribute to a more compassionate and supportive workplace environment. The civil status distribution signifies the diversity of experiences and life stages represented within the workforce. Recognizing and respecting these differences can foster a more inclusive and understanding organizational culture, ultimately enhancing employee satisfaction, engagement, and productivity[15,24].

Status of Employment Distribution

Understanding the distribution of employment statuses within the workforce is essential for workforce planning, resource allocation, and organizational decision-making[7]. It allows organizations to assess the balance between different types of employment arrangements, anticipate staffing needs, and tailor policies and practices to meet the diverse needs of employees based on their employment status. Figure 5 presents the status of employment distribution.

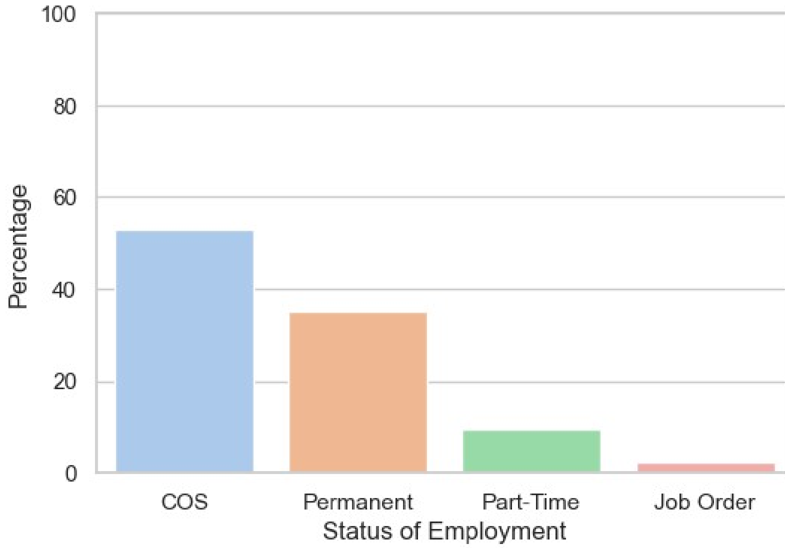


Figure 5 Status of Employment Distribution

The data reveals that the majority of employees hold positions categorized as "COS" (Contractual/Contract of Service), comprising approximately 53.08% of the workforce. This suggests that a significant portion of employees may be engaged on a contractual basis, with employment terms typically defined for a specified duration or project. Furthermore, the data indicates that approximately 35.09% of employees hold permanent positions within the organization. Permanent employment status often provides greater job security and benefits compared to contractual arrangements, and these employees may form the core workforce of the organization. Additionally, there is a smaller proportion of employees classified as "Part-Time" (approximately 9.56%) and "Job Order" (approximately 2.26%). Part-time employees typically work fewer hours than full-time counterparts and may have flexible schedules. On the other hand, job-order employees are often hired for specific tasks or projects and may have temporary employment arrangements.

Educational Level Distribution

The distribution of educational levels among administrative and academic staff indicates the diversity of qualifications and expertise present in the workforce, providing valuable insights for talent management, recruitment strategies, and professional development initiatives within the organization[10,13]. Figure 6 presents the educational level distribution of both administrative and academic staff (faculty members) of the sample workforce data.

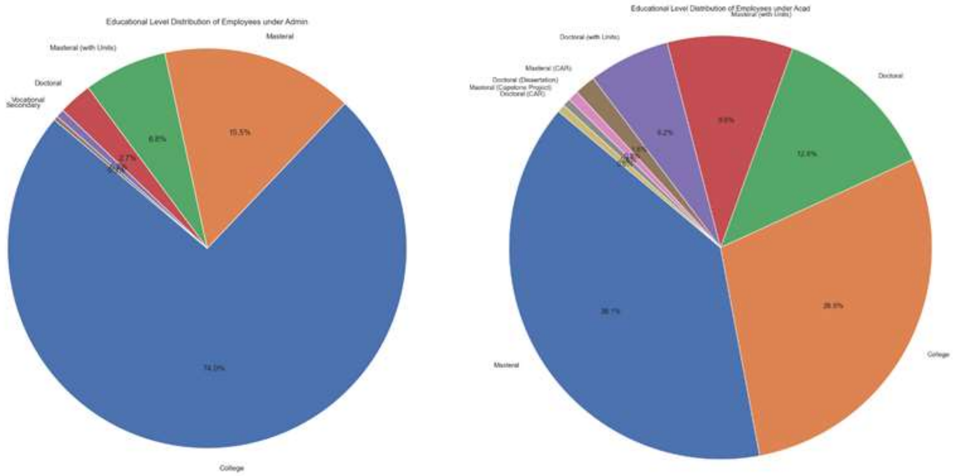


Figure 6 Educational Level Distribution

For administrative staff, the majority of administrative staff hold a college degree, indicating a foundational level of education relevant to their roles within the organization. A significant proportion of administrative staff have pursued further education beyond the college level, with 46 individuals holding master's degrees and 20 individuals having completed master's degrees (with units). This suggests a commitment to advanced studies and potentially enhances their skills and competencies in administrative roles. A smaller number of administrative staff have attained doctoral qualifications, with 8 individuals holding doctoral degrees. This indicates a high level of expertise and specialization within this segment of the workforce, potentially contributing to leadership, decision-making, and specialized administrative roles.

For academic staff, the distribution of educational levels among academic staff reflects a mix of college, master's, and doctoral degrees, with master's degrees being the most common qualification. A significant proportion of academic staff hold master's degrees, indicating advanced knowledge and expertise in their respective fields. There is also a notable presence of doctoral qualifications among academic staff, with 63 individuals holding doctoral degrees. This indicates a high level of expertise and specialization, potentially contributing to research, teaching, and leadership roles within the academic domain. Additionally, there are individuals with master's degrees (with units), doctoral degrees (with units), and specialized qualifications such as master's with a capstone project or doctoral with a dissertation or capstone project, highlighting the diverse educational pathways and areas of expertise within the academic staff.

Length of Service Distribution

The length of service distribution provides insights into the tenure and stability of the workforce, indicating the average duration of employment and the variability in tenure among employees. Figure 7 presents the visualization of the length of service of the sample workforce data.

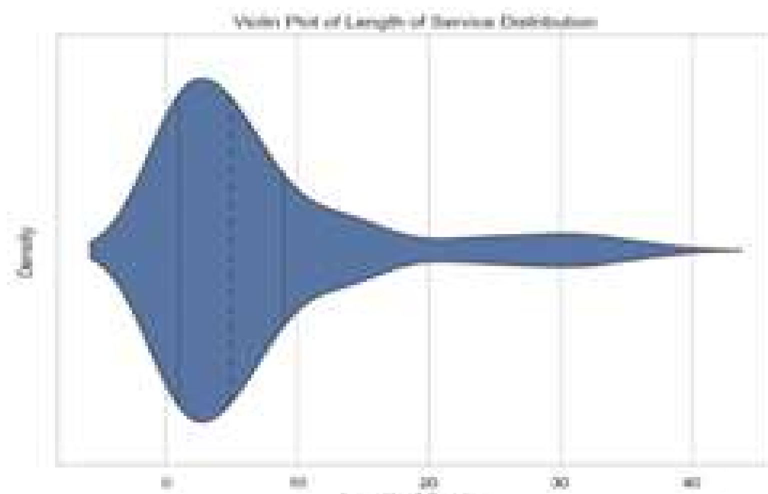


Figure 7 Violin Plot of the Length of Service

As shown in the visualization, the average length of service among employees is approximately 4.27 years. This suggests that, on average, employees have been with the organization for around four years, indicating a moderate level of stability and tenure within the workforce. With a standard deviation of approximately 6.18 years, there is considerable variability in the length of service among employees. This indicates that while the average length of service may be around 4.27 years, there is a wide range of tenures among individual employees, with some having shorter tenures and others having longer tenures. The minimum length of service observed is approximately 0.44 years, indicating that some employees have recently joined the organization. 25% of employees have a length of service of 1.31 years or less, indicating that a quarter of the workforce has relatively shorter tenures. The median length of service is approximately 2.25 years, indicating that half of the employees have tenures of 2.25 years or less. 75% of employees have a length of service of 4.08 years or less, indicating that a significant portion of the workforce has tenures of 4.08 years or shorter. The maximum length of service observed is approximately 38.88 years, indicating that some employees have been with the organization for a considerable period, contributing to the overall workforce's experience and institutional knowledge. By knowing how long employees have been with the organization, the Human Resources department can develop targeted retention strategies such as length of service recognition program and career development opportunities to retain experienced employees[27]. Further, the insights in the length of service can inform succession planning efforts by identifying employees who have been in the organization for an extended period and may be nearing retirement[22]. This allows organizations to proactively identify and develop successors for key roles. Lastly, by understanding the length of service distribution within the workforce, organizations can design engagement initiatives that cater to the diverse needs of employees at different stages of their careers[21].

b. Skills and Expertise of the Current Workforce

To uncover the skills and expertise of the both administrative and academic staff of the sample SUC in this study, Latent Dirichlet Allocation (LDA) for topic modeling and heatmap for visualization. The heatmap shown in Figure 8 and Figure 9 illustrates the distribution of skills, with intense shades indicating higher probabilities.

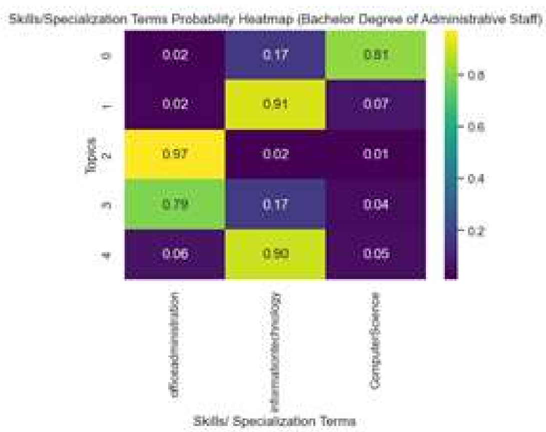


Figure 8 Skills/ Specialization Probability Heatmap (Administrative Staff)

For Administrative Staff: The heatmap visualization revealed a distinct cluster of skills and expertise among administrative staff based on their Bachelor's degree which is the minimum educational level requirement for administrative staff. High-probability skills identified by the LDA include Information Technology, Office Administration, and Computer Science with a probability of 0.93, 0.71, and 0.65 respectively. These findings underscore the importance of technological proficiency and administrative expertise within the administrative workforce.

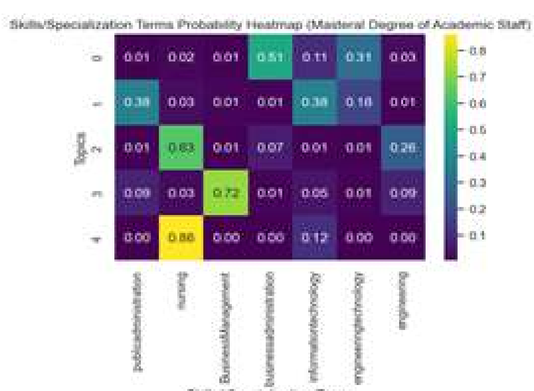


Figure 9 Skills/Specialization Terms Probability Heatmap (Academic Staff)

For Academic Staff: The heatmap visualization revealed a distinct cluster of skills and expertise among academic staff based on their Master's degree which is the minimum educational level requirement for academic staff in SUC. High-probability skills identified by the LDA include Nursing (0.78), Information Technology (0.73), Engineering Technology (0.46), Public Administration (0.27), and Business Administration (0.24).

Institutions can support faculty professional development initiatives tailored to the identified skill clusters. Training programs, workshops, and seminars can be designed to enhance expertise in key areas such as Nursing, Information Technology, and Business Administration, ensuring faculty remain abreast of industry developments and pedagogical best practices.

c. Faculty-staff and Faculty-student Ratio

The analysis of faculty-staff and faculty-student ratios offers valuable insights into resource allocation, student support, and workload management within the institution.

Faculty-staff ratio: The faculty-staff ratio provides insight into the distribution of administrative and support personnel relative to academic faculty. This was computed by dividing the number of faculty by the number of staff within the sample SUC. With the current dataset, the faculty-staff ratio is 1.69 which means there is approximately 1 staff member for every 2 faculty members. Therefore, there are more faculty members than staff members, indicating a relatively higher proportion of faculty members compared to staff members. SUCs can use this information to assess staffing needs, allocate resources effectively, and ensure optimal support for academic operations.

Faculty-student ratio: The faculty-student ratio provides insight into the distribution of academic faculty relative to the students. This was computed by dividing the number of faculty by the number of students within the sample SUC. With the current dataset, the faculty-student ratio is approximately 0.036 which means that, on average, each faculty member is responsible for overseeing the academic progress and providing guidance to about 28 students. This is higher than the standard faculty-student ratio of 1:25 [23]. While faculty members play a crucial role in mentoring and guiding students, a high faculty-student ratio may strain their ability to provide individualized attention and support. SUCs should monitor this ratio closely to maintain an optimal balance between faculty workload and student need, institutions can mitigate faculty burnout, improve job satisfaction, and ultimately enhance the teaching and learning experience, thereby safeguarding the quality of education.

d. Succession Need

To strategically place the right people in the right positions, organizations should implement succession planning[1][9]. Succession needs refers to the requirement for replacement or succession planning in an organization to ensure continuity and smooth transition in key positions, particularly those held by employees who are expected to retire or leave the organization in the future. It involves identifying critical positions and individuals within the organization and developing strategies to fill those positions with qualified successors.

In this study to determine the succession need, the percentage of the workforce that will retire in the next year and next 5 years is the basis. To obtain that percentage, the age and the years of service of each employee in the dataset were determined. Then the expected retirement age was calculated for each employee in the dataset. Based on the expected retirement age, the percentage of the employees to retire within the next year and next 5 years relative to the total workforce.

Figure 10 Succession *Need*

With the sample dataset, the analysis revealed that the percentage of the workforce that will retire in the next year and next five years is 0.36 % and 2.87 % respectively which means that there is at least one (1) employee that will retire next year and at least six (6) employees will retire in the next five years. In this connection, positions such as Professor VI will be vacated in the next year while Administrative Aider VI, Administrative Officer V, College Professor, Associate Professor V, Assistant Professor IV, and Professor III will be vacated in the next five (5) years.

In connection with the positions that will be vacated, the analysis also revealed that the expertise Demand for the next year is as follows: Bachelor's degree in Management, Master's Degree in Management, Doctoral Degree in Management Major in Human Resource Management. Further, in the next five years based on succession needs are Bachelor's Degree in Civil Engineering, Commerce-Management, Electrical Engineering, Commerce-Marketing; a Master's degree in Teaching Engineering Technology, Management, Admin, and Supervisor; a Doctorate in Development Management, Management Major in Human Resource Management, Education Major in Math.

e. Skills Gap

To assess the skills gap based on the current workforce dataset, the Jaccard similarity index was used. Jaccard similarity is a measure used to compare the similarity and diversity of two sets and is defined as the size of the intersection of the sets divided by the size of the union of the sets[11]. In this study, the tested two sets are the skills or specialization of the current workforce and the skills or specialization qualifications set by the authorities governing the SUCs in the Philippines like the Commission on Higher Education (CHED). Due to time constraints, the data included in the analysis is only the skills and specialization of the workforce under the College of Computer Studies (CCS) offering the BSIT, BSCS, BSIS, and BLIS Programs and it was compared with the set of skills/specialization qualification set by CHED through the CMO No. 25 series 2015 [5].

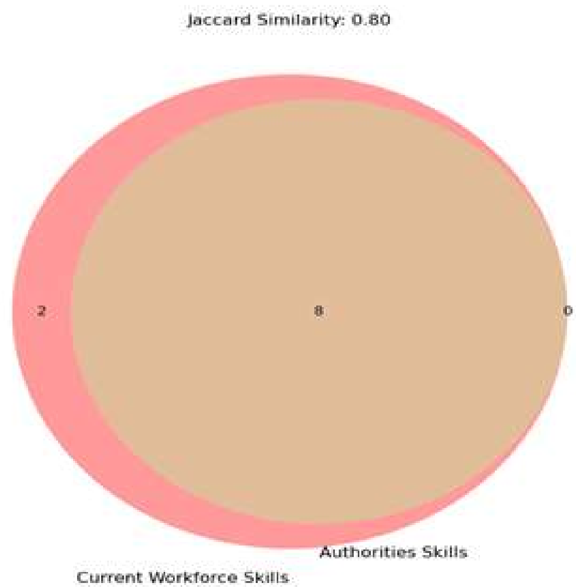


Figure 11 Jaccard Similarity Visualization

In the analysis done, a Jaccard similarity of 0.8 was revealed as shown in Figure 11. A Jaccard similarity of 0.8 indicates that there is a relatively high degree of overlap between the skills possessed by the current workforce in the College of Computer Studies and the skills set by the authorities, in the case of SUCs in the Philippines, the CHED. In other words, 80% of the skills possessed by the current workforce are also present in the skills set by CHED. Therefore, the current specialization and skill set of the CCS workforce conforms to the skillset required by CHED. This alignment can be beneficial for SUCs in complying with the regulatory and accreditation requirements such as AACCUP accreditation and accreditation done by RQAT (Regional Quality Assessment Team)[4,6].

f. Forecasting of Workforce Demand (Based on Enrolment Projection)

The forecasting of workforce demand based on enrollment projection was done by predicting first the enrolment for the next semester based on the enrollment historical data for eleven (11) semesters in the sample SUC. The prediction was done using the ARIMA model. Time series analysis like the ARIMA model was utilized in various studies on school enrolments projecting different phenomena and even workforce demand forecasting[16,26][18].

The snippet of the code shown in Figure 12 demonstrates a simple application of time series forecasting using ARIMA for enrollment prediction.

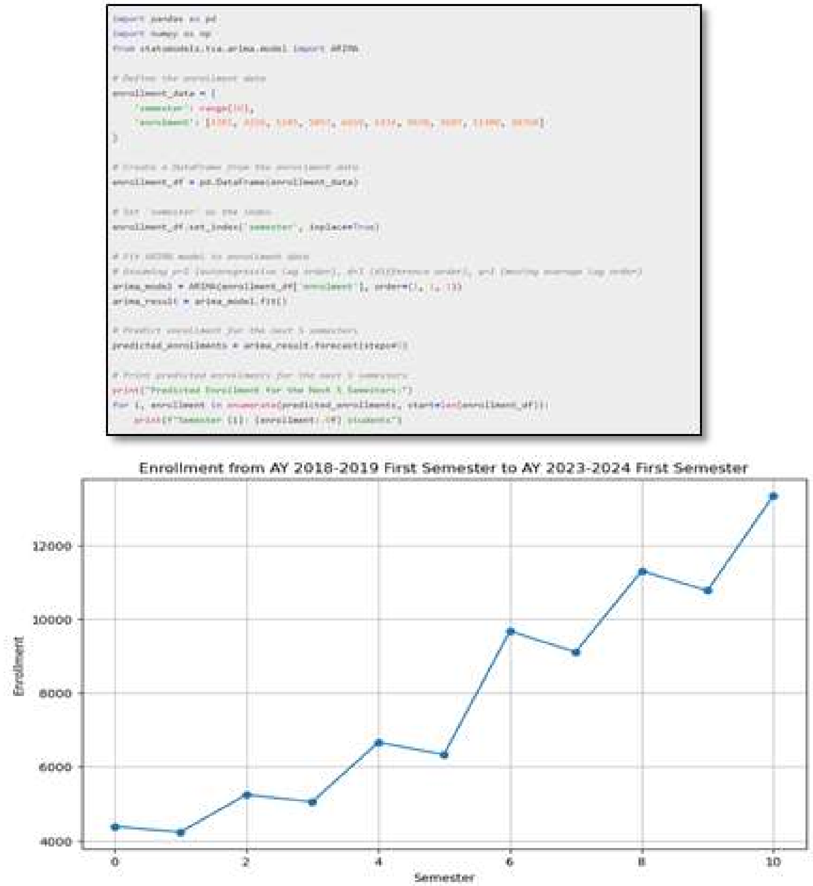


Figure 12 Code Snippet of Time Series Forecasting using ARIMA for Enrollment Prediction

This code performs enrollment prediction for the next 5 semesters using the ARIMA (Autoregressive Integrated Moving Average) model. First, the enrollment data for the last 11 semesters is defined as a dictionary and then converted into a pandas DataFrame. The 'semester' column is set as the index. Then, an ARIMA model is instantiated with the enrollment data. The parameters for the ARIMA model are set as p=1 (autoregressive lag order), d=1 (difference order), and q=1 (moving average lag order). These parameters are chosen based on assumptions or analysis of the data. Next, the ARIMA model is trained on the enrollment data using the fit() method. The model is then used to forecast enrollment for the next 5 semesters using the forecast() method with steps=5. Lastly, the predicted enrollments for the next 5 semesters are printed out, with each semester number and the corresponding predicted enrollment.

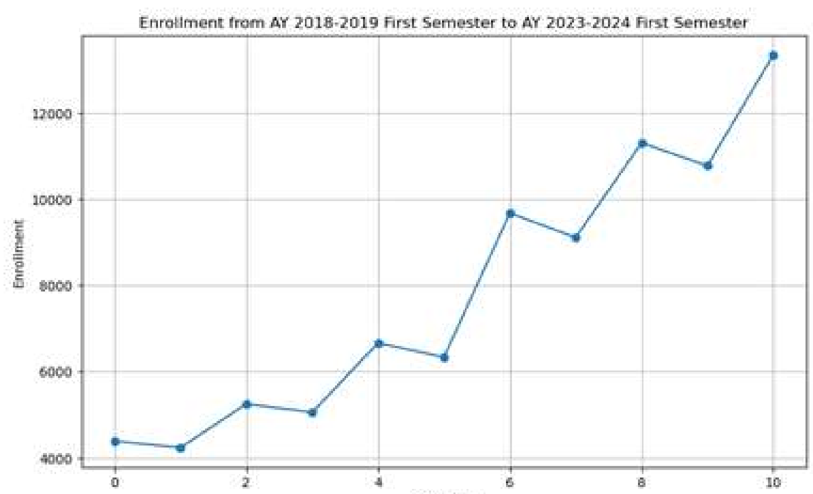
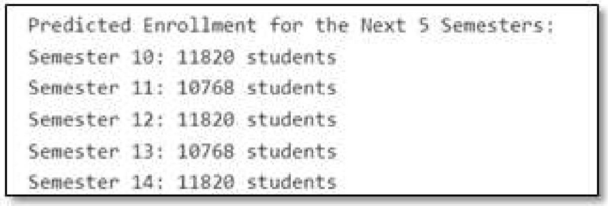


Figure 13 Time Series Plot for the Number of Enrolled Students over the Last 10 Semester

Figure 13 visualizes the enrollment data over the last 10 (0-9) semesters using a line plot. It is revealed in the visualization that there are fluctuations, both growth and decline, in enrollment numbers over time.



```
Predicted Enrollment for the Next 5 Semesters:
Semester 10: 11820 students
Semester 11: 10768 students
Semester 12: 11820 students
Semester 13: 10768 students
Semester 14: 11820 students
```

Figure 14 Prediction Result

The forecasting of workforce demand based on enrollment projection using the ARIMA model yielded insightful results. The model predicted that in the upcoming semester (semester 10), the sample SUC is expected to enroll approximately 11, 820 students in the next semester as shown in Figure 14.

To assess the accuracy of the prediction, several metrics were considered. The mean absolute error (MAE) was calculated to be 1519.00, indicating the average magnitude of the errors in the enrollment prediction. Additionally, the mean squared error (MSE) was found to be 2307361.00, providing further insight into the overall accuracy of the prediction. Lastly, the root mean squared error (RMSE) was also determined to be 1519.00, which represents the square root of the average squared differences between the predicted and observed values.

To calculate the accuracy percentage of the model from the given Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), these error values were compared to the actual values of the dataset. However, these metrics alone do not directly provide an accuracy percentage so the Mean Absolute Percentage Error (MAPE) was computed to get a sense of the accuracy in percentage terms.

The formula for MAPE is:

$$\text{MAPE} = (1/n)\Sigma\,|((\text{Ai} - \text{Fi}))/\text{Ai}| * 100$$

Where Ai and Fi are the actual values and are the forecasted values. Using MAE as an approximation for the average error magnitude:

$$\text{MAPE} \approx (\text{MAE} / \text{Average Actual Value}) \times 100$$

The average actual enrollment value is denoted as Ā.

Given:

Mean Absolute Error (MAE) = 1519.00

Average actual enrollment value Ā= 13,339

$$\text{MAPE} = (\text{MAE} / \bar{\text{A}}) \times 100$$

MAPE = (1519.00 / 13339) × 100

$$(1519.00 / 13339) \approx 0.1139$$

So, the Mean Absolute Percentage Error (MAPE) is approximately 11.39%. With this, the accuracy was computed as shown below:

$$\text{Accuracy} = 100\% - \text{MAPE}$$
$$\text{Accuracy} = 100\% - 11.39\%$$
$$\text{Accuracy} = 88.61\%$$

Based on the calculations, the accuracy of the model, when the actual enrollment value is 13,339, is approximately 88.61%. This means that the model's predictions are, on average, about 11.39% off from the actual values, which translates to an 88.61% accuracy in predicting enrollment numbers.

These prediction accuracy metrics offer valuable insights into the reliability of the ARIMA model for forecasting workforce demand based on enrollment projections. While the model demonstrates a reasonable level of accuracy, it is important to interpret these metrics within the context of the specific forecasting task and the inherent uncertainties associated with enrollment projections.

Table 1 Estimated Faculty Demand in the Next Five Semesters

Predicted Enrolment for the next 5 semesters	Estimated Faculty Demand (1:25)	Estimated Administrative Staff (3:1)
11820	472.8 (473)	157.6 (158)
10768	430.72 (431)	143.57(144)
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With the projected enrollment number for the next semester as shown in Table 1, it is estimated that approximately 473 faculty members will be required to maintain the standard faculty-student ratio of 1:25[23]. Further, it is also estimated that for the next semester, approximately 158 administrative staff is needed to maintain the recommended faculty-staff ratio of 3:1[25]. This estimation provides valuable guidance for workforce planning and resource allocation within the college, ensuring that adequate support and guidance can be provided to students to facilitate their academic success.

4] CONCLUSION

This study explored the complexities of workforce planning within SUC, employing a multifaceted approach encompassing exploratory data analysis (EDA), predictive modeling, and strategic interpretation of findings. Through a comprehensive examination of workforce demographics, skills and expertise distribution, faculty-staff ratios, faculty-student ratio, succession need, and enrollment projections, several key insights have been unearthed, leading the way for informed decision-making and strategic resource allocation.

In conclusion, the result of this study emphasizes how crucial data-driven decision-making is for guiding strategic workforce planning programs at educational institutions such as SUCs. SUCs may foster a culture of innovation and continuous improvement, optimize resource allocation, and proactively address workforce concerns by utilizing insights obtained from exploratory data analysis and predictive modeling.

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7] Data Availability:

Due to ethical concerns and confidentiality of the used data in this study, data sharing is not applicable to this article.

8] Conflict of interest

The authors declare that there is no conflict of interest.

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