The Eurasia Proceedings of
Educational & Social Sciences (EPESS)
ISSN: 2587-1730

The Eurasia Proceedings of Educational & Social Sciences (EPESS), 2024

Volume 39, Pages 162-170

IConSE 2024: International Conference on Science and Education

Bayesian Correlation between Cumulative Grade Point Average and Employment

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Abstract: Many believe a high CGPA (Cumulative Grade Point Average) correlates with better employment opportunities. This belief stems from the idea that a high CGPA reflects a student's dedication, intelligence, and ability to perform well under academic pressure, qualities often valued by employers. However, it is also recognized that practical skills, experience, and personal attributes play crucial roles in securing a job. Is a high CGPA enough of a metric to open job opportunities? To address this question, the study analyzes the relationship between alumni's Cumulative Grade Point Average (CGPA) and employment prospects. The research was conducted at the American University of Kurdistan (AUK), and the data was obtained from the Admissions and Registration and the Office of Advancement. The goal is to understand whether academic performance, as measured by CGPA, significantly influences the employability of graduates in the architectural engineering field. Thus, the study employs a robust methodology, using Bayesian Correlation to provide substantial evidence per the guidelines requested by the New England Commission of Higher Education (NECHE). The data involves a review of academic records and survey responses to employment data from AUK's architectural engineering alumni. Findings suggest a negative anecdotal correlation between CGPA and employment, indicating that students with higher CGPAs do not necessarily secure employment in their field of study soon after graduation.

Keywords: Cumulative grade point average, Employment data, Bayesian correlation

Introduction

Many employers and post-graduate programs still use the cumulative grade point average (CGPA) as a metric of the graduate's performance despite the decades-long implementation of outcome-based education (OBE) in engineering education. CGPA indicates the general abilities of a graduate but needs to be more specific to identify whether alumni's skills can fulfill the job requirements. Thus, the Architectural Engineering industry wants to see the potential of graduates with soft and hard skills.

The growing competitiveness in the job market requires these abilities to handle the job's complexity; that is a significant reason why universities offer engineering programs to employ the OBE framework and prepare graduates to be job-ready upon graduation. Despite this, recent literature has revealed that many employers struggle to get suitable graduates for a specific engineering job, which echoes the incompetence of CGPA to show what the graduate knows and can do upon graduation. The situation raises fundamental questions: "Do graduates with low CGPA possess inadequate skills to be job-ready? Moreover, "Do graduates with high CGPA possess adequate skills to be job-ready?" (Gamboa et al., 2017). This study compares CGPA and Employment status in the field to determine whether they are convergent or divergent. Therefore, the result of this paper can serve as a basis for whether CGPA can still be considered a valid job performance metric.

Various studies have explored academic performance and employment in engineering. For instance, Gamboa (2017) found that a good CGPA is often critical to securing employment. However, it may only partially reflect an individual's skill level, supported by Mari (2019), who noted a gap between architecture graduates' skills and those required by employers (Mari et al., 2019). Wao's (2022) study in construction management found a

- Selection and peer-review under responsibility of the Organizing Committee of the Conference

positive correlation between undergraduate CGPA and professional certification exam scores, suggesting a potential link between academic performance and employability (Wao et al., 2022).

Another study examines the effect of GPA on graduating students' wages using data from an elite university in China. The Ordinary Least Squares (OLS) regression results indicate that GPA positively and significantly impacts average wages. As GPA increases by 1 unit, the starting monthly wage increases by 29.6 percent on average. Moreover, the salary in the survey year 3–5 years after graduation (current wage) hovers by 25 percent. The study suggests that the high GPA associated with high wages should be mainly due to the human capital effect (Zou et al., 2022).

The American University of Kurdistan (AUK) was founded in 2014 as a non-profit higher education institution that is seeking accreditation from The New England Commission of Higher Education (NECHE) (New England Commission of Higher Education, 2023) to improve Quality Assurance, Credit Transfer, Institutional Improvement, Public Assurance and, Support and Guidance. These topics serve both AUK's Mission-Vision and NECHE's criteria, which require substantial evidence to ensure the institution meets its standards for accreditation. One of the critical aspects is the Achievement of Purposes. The institution must demonstrate that it can achieve its mission. Therefore, the study can be a good model and address the Bayesian correlation between CGPA and employment success of the industry's Department of Architectural Engineering graduates.

The Evolution of Bayesian Correlation: A Historical Perspective and JASP

Bayesian statistics, a branch of mathematics and statistical inference, has significantly influenced how we understand and interpret data. At the heart of Bayesian statistics lies Bayes' theorem, a fundamental principle that allows us to update our beliefs in light of new evidence.

The Beginnings: Bayes and Laplace

The story of Bayesian correlation begins with Reverend Thomas Bayes, an English statistician and philosopher, who postulated a specific case of what we now know as Bayes' theorem in a paper published posthumously in 1763. However, Pierre-Simon Laplace, a French mathematician and astronomer, developed the Bayesian interpretation of probability in several papers from the late 18th to the early 19th centuries. Laplace's work laid the groundwork for a robust statistical methodology (Fienberg, 2006).

The 20th Century: Growth and Expansion

Throughout the 20th century, Bayesian statistics underwent significant expansion. Developing hierarchical and nonparametric models and general computing tools allowed the routine use of non-conjugate distributions. This period also saw the incorporation of model checking and validation in an iterative data analysis process, marking a shift from traditional subjectivist and objectivist frameworks to ideas based on prediction and falsification (Gelman, 2022).

Modern Bayesian Correlation

In recent years, Bayesian approaches to data analysis have gained popularity as an alternative or supplement to traditional hypothesis testing. Unlike P values, Bayesian analyses directly measure the strength of evidence for and against a study hypothesis, offering a more intuitive and less prone to misinterpretation form of results (Nuzzo, 2017). This has been particularly useful in exploring the relationship between two quantitative variables, where Bayesian correlation comes into play. As part of the broader Bayesian statistical framework, Bayesian correlation continues to evolve and adapt. It offers a flexible and powerful approach to applied statistics and remains an invaluable tool for a general understanding of statistics.

Currently, Bayesian statistics has led to extensive research in Bayesian methodology and the use of Bayesian methods to address complex questions in diverse application areas such as astrophysics, criminal justice, education, weather forecasting, and health care policy. As we look to the future, Bayesian methods will continue to influence how we analyze and interpret data.

Bayesian Analysis in This Study

Bayesian analysis is a statistical paradigm that uses probability statements to answer research questions about unknown parameters. For instance, in the study context, a Bayesian analysis could quantify the uncertainty or confidence in the correlation between CGPA and employment (Sosa & Buitrago, 2021). Thus, Bayesian analysis allows the incorporation of prior knowledge, such as previous studies or expert opinion, into the statistical model (M. D. Lee, n.d.). This can be particularly useful when the data is sparse, or we want to combine results from different sources.

Probability distributions typically express scientific hypotheses to observe scientific data. These distributions correlate with unknown quantities called parameters. The model parameters are stated by placing a probability distribution in the Bayesian paradigm. The "prior distribution" is often written as $p(\theta)$, which represents our pre-existing knowledge or belief about an event before new data. In our case, it could be a belief about the correlation between CGPA and employment based on previous studies or expert opinion, which is addressed in the introduction of this section. The "likelihood" is a proportional distribution of the observed data, depicting how well our data matches our predictions. It is the probability of observing the data given our prior beliefs. When new data y becomes available, the model parameters are written as $p(y|\theta)$.

This information can be combined with previous information to increase the probability of an update. In this case, the distribution is called the "posterior distribution." Our belief has been updated after integrating the new evidence. Thus, it evolves from the prior and the likelihood, and It represents our updated belief about the correlation between CGPA and employment after observing the data from the study. All Bayesian inference is based on posterior distribution. To express precisely, the posterior is proportional to the prior times the likelihood,

$$p(\theta|y) = \frac{p(\theta)p(y|\theta)}{\int_\theta \ p(\theta)\, p(y|\theta)\mathrm{d}\theta}$$

In Bayesian analysis, the data is used to update our prior beliefs to yield the posterior beliefs. This is done using Bayes' theorem. The likelihood function of the data and the parameter of interest plays a vital role in this updating process (Lecture 20-Bayesian Analysis, n.d.). The likelihood quantifies how consistent the data is with the different values of the parameter under consideration. The prior and likelihood are combined to form the posterior distribution, which is then normalized to ensure a valid probability distribution (The Prior, Likelihood, and Posterior of Bayes' Theorem, n.d.). Theoretically, the posterior distribution is always available, but the required analytic computations are often intractable in realistically complex models. During the late 1980s and early 1990s, Methods for drawing samples from the posterior distribution became widely acceptable (Cowles et al., 2019).

First developed at the University of Amsterdam, JASP is a popular software program for conducting and teaching statistics. JASP is already presenting a full-fledged replacement for popular commercial software programs such as SPSS and Minitab. Many of the more prominent universities in the Netherlands have already switched to JASP. Over 290 universities across 67 countries use JASP in their curricula globally (Wagenmakers, 2018).

Data Collection and Model Building

AUK's Department of Architecture's alumni data, including student identification numbers, CGPAs, and employment status in the architecture field, were compiled in an Excel file. There were 44 AE graduates from 2020 until spring 2024. Based on the data, two variables, CGPA and the Employment Status in the Architecture Field, are defined. The correlation between these two variables can be used to determine how these pairs of variables are associated. For instance, continuous or ordinal data make this correlation appropriate for quantifiable data in which numbers are meaningful. In this case, CGPA is defined as continuous, and Employment Status is defined as ordinal data. A parametric (Pearson's) correlation coefficient is reported as a frequentist correlation, and confidence intervals and p values are replaced by Credible Intervals (CI) and Bayes factors (BF). Moreover, there are (H_0) and (H_1) hypotheses. The test addresses whether the data are more likely to occur under the null hypothesis (H_0), meaning there is no linear association between the two variables. Under the alternative hypothesis (H_1), if there is an association between the two variables. Thus, observing the data allowed the application of Bayes' theorem to have the posterior probability of both hypotheses.

Assumptions

There are four critical assumptions for the correlation to provide valid results in Bayesian analysis:
a. Linearity: This assumption states that a linear affiliation exists between the two studied variables. In other words, if you plot the two variables on a graph, the points should roughly form a straight line. If the relationship is not linear, then the correlation coefficient may not accurately represent the strength and direction of the relationship (Kruschke & Liddell, 2018).
b. Independence: The observations should be independent of each other. This means that the value of one observation does not influence or affect the value of different observations. This is important because if observations are not independent, it can lead to misleading results (J. Lee et al., 2020).
c. Homoscedasticity: This assumption states that the discrepancies along the line of best fit remain similar as the line is followed. In other words, the spread of residuals (differences between observed and predicted values) should be roughly equal across all stages of the independent variables (Yang et al., 2019).
d. Normality: This assumption states that the data should follow a normal distribution. This is important because many statistical tests rely on normality for valid results. In the context of Bayesian analysis, this assumption often applies to the prior and posterior distributions (van Doorn et al., 2021).

It is important to note that these assumptions are not always strictly required in Bayesian analysis. Bayesian methods can be flexible and handle violations of these assumptions better than traditional statistical methods. However, checking these assumptions can still be a decent practice to ensure the quality and reliability of your results.

Experimental Setup

Several critical aspects need to be considered in the experimental setup, such as;
In JASP software, specifying a prior distribution for Bayesian analysis involves defining how much weight is intended to give to different parameter values before observing the data. This is essential because it reflects the prior beliefs or knowledge about the parameters. The prior distribution process starts by selecting the Bayesian analysis to perform, such as a t-test, ANOVA, or regression. In this study, regression has been chosen. The next step is setting the priors. For each parameter, a prior distribution can be set. JASP often provides default priors, but if the researcher has prior knowledge, this can be incorporated to specify informative priors (Heo &van de Schoot, 2020). In our case, the stretched beta prior is set to 1 to express all correlations between -1 and +1 that are given an equal prior probability. The third step is adjusting the parameters; depending on the analysis, we may need to specify the prior distribution's mean, standard deviation, and other parameters. For instance, we would set priors for the intercept, regression coefficients, and residual variance in a Bayesian regression. In our context, default priors have been applied (*JASP_Bayes_default_priors_version1*, n.d.). JASP also allows for more advanced prior specifications using JAGS (Just Another Gibbs Sampler), where we can enter custom prior distributions for more complex models. Thus, the study does not require more advanced prior specification. Lastly, JASP has a built-in visualization tool named Shiny App to help the researchers see the effects of different prior specifications on any model. Thus, our study used this tool. Therefore, the choice of prior can significantly affect the results of Bayesian analysis, especially in cases with limited data. It is essential to consider the prior distribution carefully and justify choices when reporting results.

JASP software offers a variety of prior distributions for Bayesian analysis, allowing users to choose the one that best fits their prior knowledge or beliefs about the parameters. The types of prior distributions available in JASP include:

Continuous Distributions:
- Normal: Used for parameters that can take on any real value, often with a mean of 0.
- Student’s t: Similar to the normal distribution but with heavier tails, functional when expecting outliers.
- F-distribution: For ratios of variances, often in the context of comparing group variances.
- Chi-squared: Typically used for variance components.
- Beta: Ideal for parameters that are proportions bounded between 0 and 1.
- Gamma: Suited for positive continuous variables, like rates.
- Inverse gamma: Often used as a prior for variance parameters.
- Exponential: For non-negative parameters, commonly used for rates or time until an event.

Discrete Distributions:
- Bernoulli: For binary outcomes, like success/failure.

- Binomial: For the number of successes in a fixed number of Bernoulli trials.
- Negative binomial: For counting data, it represents the number of failures before a specified number of successes.
- Poisson: For count data, particularly for modeling the number of events occurring in a fixed interval of time or space (Simon Kucharsky, 2020).

In our case, the distributions are continuous, and the parameters are uniform. The likelihood of the data distribution is handled through various statistical analyses based on probability distributions in JASP. The analysis is Regression, as addressed above. JASP used the likelihood function with the prior distribution to update the beliefs about the parameters, resulting in the posterior distribution. The software computes the likelihood of the observed data under various parameter values and updates the prior beliefs to form the posterior beliefs.

JASP settings in the statistics applied as Pearson's ρ, alternative hypotheses = correlated, reporting BF_{10} that represent the Bayes factor supporting the alternative hypotheses, flagging supported correlations and plots of the correlation matrix and posteriors under H_1. Therefore, experimental setup considerations are applied to run the correlation (Goss-Sampson et al., 2020).

Result and Analysis

Interpretation and discussion of the Bayesian analysis results could begin with the Bayesian Pearson correlations. Below is the population sample size n=44, Pearson's ρ=-0.288, and BF_{10}=1.068.
Table 1. Bayesian Pearson Correlations by Author

Table 1. Bayesian Pearson Correlations

	n	Pearson's ρ	BF_{10}
CGPA - Employment Status in the Architecture Field	44	-0.288	1.068

* $BF_{10} > 10$, ** $BF_{10} > 30$, *** $BF_{10} > 100$

Pearson's ρ value (-0.288) shows an anecdotal negative correlation between the two variables. Bayesian correlation between CGPA and Employment Status in the Architecture Field reports low BF (1.068) values in the anecdotal evidence range. Thus, the Bayesian approach is more conventional and only flags significance when the evidence is as strong as BF_{10} >10.

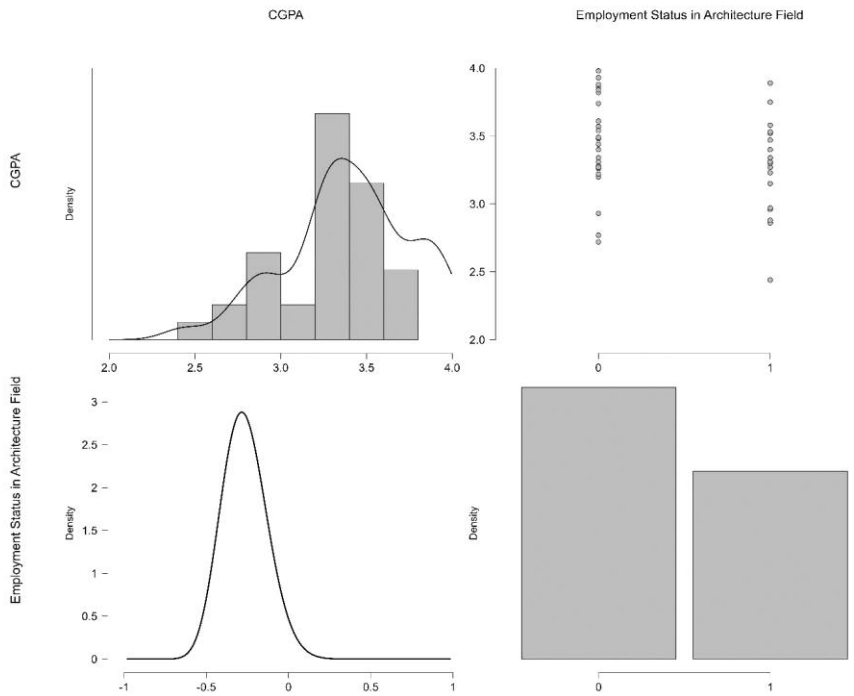

Figure 1. Bayesian correlation matrix plot by author

The provided Figure above contains four graphs that can be analyzed from a Bayesian perspective:

- Histogram & PDF (Probability Density Function) Curve: The histogram shows the distribution of CGPAs, which can be modeled using a Bayesian approach to estimate the underlying probability distribution. The overlaid PDF curve suggests a prior belief about the distribution, which can be updated with observed data to obtain a posterior distribution. The study shows a setup for displaying the Normal distribution. Thus, the first upper left plot displays the CGPA density and probability associated with the interval between 2 and 4.
- Scatter Plot: This upper right-located plot illustrates the relationship between CGPA and employment status. A Bayesian correlation analysis could be used here to determine the probability of employment given a certain CGPA, incorporating prior knowledge or assumptions about the architecture industry.
- Kernel Density Estimate (KDE): KDE is used to estimate the continuous random variable of the probability density function. In a Bayesian context, this could represent the prior or posterior belief about the distribution of CGPAs.
- Bar Chart: By comparing employment statuses, Bayesian methods could analyze the probability of each employment status category given the data, potentially considering prior information about employment in architecture.

Therefore, the Bayesian Correlation Matrix provides employment Status and CGPA Plot that shows the linear relationship between two variables. In the status, 1 represents employment, and 0 represents unemployment status. Moreover, the higher CGPA density and slightly negative employment correlation supplement the results.

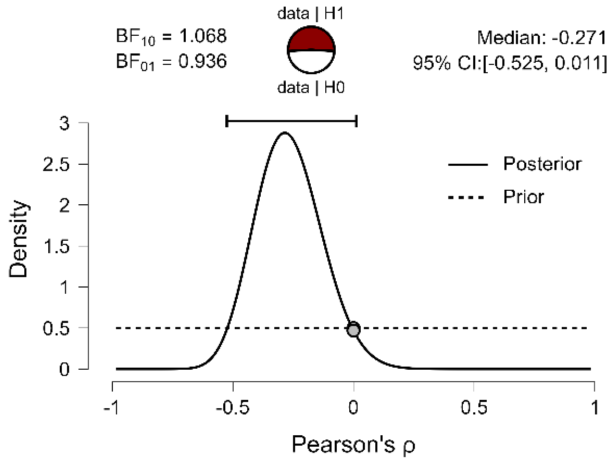

Figure 2. Prior and posterior plot by author

Assuming a negative correlation, the posterior-prior plot for CGPA and Employment Status shows the data fully distributed to the left of ρ = 0, with a median value of -0.271, as the Bayes factor is low. The solid line in the previous plot shows the posterior distribution (based on the dataset), and the dashed line represents an even prior distribution. Each of the distributions has a grey dot at the zero-effect size. The prior distribution is lower than the posterior distribution. Thus, the Bayes factor supports the alternative hypothesis (H_1). The last step is to check how robust the analyses are. Figure 3 below illustrates the relationship between the Bayes Factor (BF_{10}) and the standardized beta prior width (k). Thus, we need to recap the following metrics to understand the graph more deeply.

- Bayes Factor (BF_{10}): This metric is used in Bayesian statistics to quantify the evidence for one statistical model over another. In this case, BF_{10} compares the evidence for the alternative hypothesis (H_1). against the null hypothesis (H_0).
- Standardized Beta Prior Width (k): This represents the spread of the prior distribution over the standardized beta coefficient. A smaller k indicates a more concentrated prior, suggesting stronger prior beliefs about the value of the beta coefficient.
- Evidence for Hypotheses: The graph is annotated to show different levels of evidence. A BF_{10} greater than 1 indicates evidence for (H_1), while a BF_{10} less than 1 indicates evidence for (H_0). The annotations also categorize the strength of the evidence as “Anecdotal” or “Moderate” based on the (BF_{10}) value.

- Key Points: The graph highlights two key points:
  - At k = 0.1231, the max (BF_{10}) is approximately 1.944, suggesting moderate evidence for (H_1).
  - At k = 1, the user prior: (BF_{10}) is approximately 1.068, indicating anecdotal evidence for (H_1).

This graph visualizes how the choice of prior can affect the Bayes Factor and, consequently, the interpretation of statistical evidence in favor of hypotheses. It underscores the importance of carefully considering prior distributions in Bayesian analyses. Moreover, the robustness analysis below allows us to inspect the BF obtained if the alternative model was specified differently. Thus, the analysis shows the outcomes of identifying a range of prior values from 0 to 2 (Fienberg, 2006).

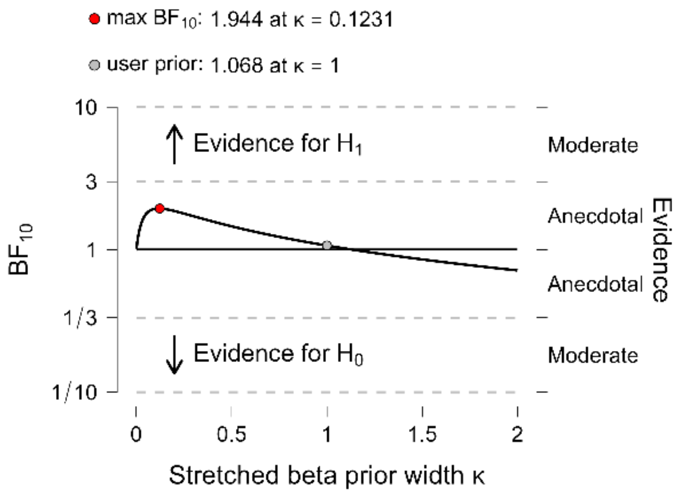

Figure 3. Bayes factor robustness check by author

To sum up, there is a weak correlation between CGPA and employment (k = 0.1231) using a one-sided alternative hypothesis that was complemented by a Bayes factor BF_{10} = 1.944, indicating an anecdotal likelihood ("evidence") of this occurring in the H_1 rather than H_0 and the prior width was set as 1.0 in JASP. Thus, the results are insensitive to changes in the prior width, and the Bayes factor is relatively stable except for minimal prior widths. Therefore, it confirms the analysis's robustness.

Limitations

This study is based on all graduates (n=44) between Fall 2020 and Spring 2023 Convocations. It must be considered when interpreting the findings of this study and in any further research or interventions to increase the number of alumni in the department. AE is growing and has 230 active students at the time of this study, with 300 forecasted active students at the close of Fall 2024. Thus, the sample size can be increased for the following assessments. It is important to note that these limitations should be considered. The other variables, such as salary, date of birth, and gender, were not in the scope of the study. Therefore, they should not be viewed as invalidating the findings but as providing areas for further exploration and research. Ultimately, architectural engineering success is achieved by getting a job in the field.

Conclusion

The outcome of this research can contribute significantly to understanding academic performance and employability, particularly in architectural engineering. It provides valuable insights for educational institutions, students, and employers, emphasizing the need for a holistic approach to education that poises academic achievement with practical skills and experiences. The study underscores the commitment of AUK's Department of Architectural Engineering to continually enhance its teaching methods and curriculum to prepare students for the architecture industry. It also sets a precedent for similar studies in other departments and universities, promoting a culture of evidence-based decision-making in higher education. In conclusion, while CGPA is crucial, a multifaceted approach to education that includes practical experience and skill development is essential for improving employability in the architectural engineering sector. Thus, the study can encourage educational institutions to explore different assessment methodologies.

Data Availability Statement

The dataset analyzed for this study is available and can be provided by the author upon request.

Scientific Ethics Declaration

The author declares that the scientific, ethical, and legal responsibility of this article published in EPESS Journal belongs to the author.

Acknowledgments or Notes

* This article was presented as an oral presentation at the International Conference on Science and Education (www.iconse.net) held in Antalya/Turkey on November 13-16, 2024

* The author would like to thank Dr. Hussein Zekri for the equation peer review, Dr. Masoud Muhammed Hassan for the Bayesian Analysis review, Mr. Ibrahim W. Hussein (Admissions and Registration) for providing CGPA, and Ms. Farah Ali (Office of Advancement) for the alumni employment data. Their collaboration fosters AUK's pursuit of its mission towards NECHE accreditation.

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To cite this article:

Hakgudener, S. (2024). Bayesian correlation between cumulative grade point average and employment. *The Eurasia Proceedings of Educational and Social Sciences (EPESS), 39*, 162-170.