KARYA ILHAM PUBLISHING
CONNECTING MINDS, BRIDGING IDEAS, INSPIRING READERS

Journal of Advanced Research in Social and Behavioural Sciences

Journal homepage: https://karyailham.com.my/index.php/jarsbs/index
ISSN: 2462-1951

Ensuring Robustness in PLS-SEM and Regression: Evaluating Multivariate Assumptions in the Study of Innovative Work Behaviour among Malaysian Academics

Siti Rosnita Sakarji[1], Zarina Begum Ebrahim[1,*], Irzan Ismail[1], Erne Suzila Kassim[1]

[1] Faculty of Business and Management, University Teknologi MARA, Malaysia

ARTICLE INFO

Article history:
Received 31 December 2025
Received in revised form 23 February 2026
Accepted 30 April 2026
Available online 18 May 2026

ABSTRACT

This study presents a methodological examination of multivariate assumptions, including normality, linearity, homoscedasticity, multicollinearity, and residual independence, within a behavioral research model focused on innovative work behavior (IWB) among academics in Malaysian higher education institutions (HEIs). Thus, the purpose of this study is to comprehensively assess whether important multivariate assumptions underlying multiple regression and PLS-SEM are satisfied when modelling IWB among academics. Using survey data collected from 389 permanent academic staff, IWB was modelled as the primary outcome variable, predicted by psychological empowerment, flexible work arrangements, perceived organizational support, knowledge sharing, transformational leadership and individual innovation capability. The model estimate was performed using composite construct scores obtained from verified Likert-scale measures, which were examined using SPSS Version 29 for assumption testing and SmartPLS 4.0 for structural modeling. Model estimation was performed using composite construct scores obtained from verified Likert-scale measures, examined using SPSS Version 29 for assumption testing and SmartPLS 4.0 for structural modelling. The findings indicate that the data met all essential multivariate assumptions, except for multivariate normality, which is a key assumption. However, the other assumptions, including linearity, homoscedasticity, multicollinearity, and residual independence, were met. By applying this approach, it improves the validity of the ensuing inferential analysis. Thus, the current study methodologically contributes by providing a structured, contextual framework for assumption testing in higher education research, serving as a reference for other studies in the behavioral and social sciences. It is, therefore, recommended that all researchers across behavioral and social sciences, management, and all relevant disciplines, adopt and adhere to this framework for testing assumptions for their data to be applicable for multivariate data analysis.

Keywords:
Multivariate assumptions; PLS-SEM; regression analysis; innovative work behavior; higher education

* *Corresponding author.*
E-mail address: zarina148@uitm.edu.my

https://doi.org/10.37934/arsbs.43.1.147157

1. Introduction

Innovative Work Behaviour (IWB) in academia has garnered increased attention as higher education institutions (HEIs) strive to maintain competitiveness and adapt to a rapidly evolving knowledge economy [6]. Moreover, HEIs have emerged as crucial contributors to knowledge generation and dissemination, and promoting innovation among academics is essential for achieving institutional objectives [1]. In Malaysia, supporting academic innovation is aligned with national development goals and correlates with the fourth Sustainable Development Goal, which emphasizes the importance of educational excellence [5]. IWB encompasses the generation, promotion, and execution of novel ideas that improve organizational performance [15]. Thus, examining the factors that drive academic IWB is critical for promoting a culture of innovation, flexibility, and information-driven growth in Malaysian universities.

Academics in Malaysian HEIs are expected to serve as catalysts for innovation, including research, teaching, as well as administrative and leadership functions. Thus, recognizing the psychological and organizational factors influencing IWB has attracted considerable academic interest [2,14]. Drawing on literature from innovation in higher education, the current research considers six independent variables, namely psychological empowerment, flexible work arrangements, perceived organizational support, knowledge sharing, transformational leadership, and individual innovation capability.

Despite numerous empirical studies examining factors influencing IWB using statistical models such as regression and structural equation modelling (SEM), a notable gap remains in the literature concerning the insufficient evaluation of the multivariate assumptions underpinning these parametric techniques [13,26]. Violating assumptions like normality, linearity, or homoscedasticity might undermine the validity of regression or SEM outcomes [8,20]. Thus, in behavioral science and educational research, where models can encompass numerous aspects and intricate relationships, confirming these assumptions is crucial for deriving meaningful conclusions [12,20].

This study intends to address the research gap in the IWB literature by conducting a comprehensive review of the assumptions in a multivariate analysis of the drivers of IWB among academics in Malaysian higher education institutions. Specifically, the proposed study aims to evaluate assumptions in a multivariate analysis in terms of normality of the multivariate distribution, normality of the residuals, linearity, homoscedasticity, multicollinearity, and independence in the data. Therefore, the present study seeks to establish a research framework for the primary investigation by offering a comprehensive assessment of assumptions in a multivariate analysis. Additionally, it intends to serve as a guide for researchers seeking to promote research best practices in the study of innovation and organizational behaviour. The study aims to strengthen the credibility of the research process, ensuring that each tested hypothesis or conducted mediation analysis yields precise statistical data.

2. Literature Review

2.1 Innovative Work Behaviour

The growing rivalries of the higher education industry require universities to cultivate IWB among academics to sustain relevance and enhance institutional performance [19]. IWB refers to the intentional cultivation, demonstration, and use of innovative ideas inside a team, company, or role to enhance performance [15]. In this study, six independent factors were selected based on the literature on IWB in higher education. Besides, the choice of the construct is also grounded in both theoretical and empirical evidence. These constructs are theoretically connected to IWB through Social Exchange Theory, Social Cognitive Theory and Self-Determination Theory, which highlight how organizational support, leadership, empowerment and individual competencies foster innovation-related behaviour. These variables are psychological empowerment (PE), flexible work arrangements (FWAs), perceived organizational support (POS), knowledge sharing (KS), transformational leadership (TL), and individual innovation capability (IIC). These constructs have been extensively used in IWB literature [3,9,11,24,25,27].

PE refers to the process by which an individual cultivates motivation and bolsters their self-assurance in the workplace [28].bFWA can be described as working arrangements that may provide flexibility to the "location" of work or to the "timing" of work completion [10]. POS refers to employees' perceptions that their superiors care about them and appreciate their efforts to the organisation [7]. KS refers to the process of knowledge transfer, where individuals spread and build upon their tacit as well as explicit knowledge [23]. TL represents the process of inspiring and encouraging subordinates to reach goals and innovate [22]. Finally, Lei *et al*., [21] identified IIC as the "extent of effort" exercised by individuals to innovate.

2.2 Multivariate Assumption Testing in Behavioural Research

Various multivariate statistical techniques, including multiple regression and PLS-SEM, depend on some crucial assumptions concerning the accuracy of estimates and inferences [12]. However, though PLS-SEM has been considered as less sensitive to violations of distributional assumptions, researchers point out that the validation of assumptions strengthens the believability and trustworthiness of findings [13]. Even though regression analysis and SEM have been widely used in IWB literature, there has been an emphasis on hypothesis testing with no discussion on related assumptions in previous literature [13]. In behavioural and educational research, breaches of assumptions such as non-normality, non-linearity, heteroscedasticity, multicollinearity, and residual dependence frequently occur due to the use of complex psychological conceptions and survey-derived data [4]. However, many empirical studies on IWB among academics report substantial findings without clearly documenting whether these assumptions were tested or satisfied, raising concerns about the robustness and replicability of reported results. The key assumptions are multivariate normality, normality of error terms, linearity, homoscedasticity, multicollinearity and independence of residuals [12].

First, normality pertains to the distribution of variables and residuals. Although PLS-SEM does not necessitate regularly distributed data, normality is significant in regression and enhances the robustness of bootstrapping in SEM [16]. Normality can be evaluated by skewness and kurtosis statistics, histograms, and formal assessments such as the Kolmogorov-Smirnov and Shapiro-Wilk tests [4,13,29]. The Mardia (1970) test can be employed to statistically evaluate multivariate skewness and kurtosis. Skew measures how uneven the score distribution is, while kurtosis measures the highest point of the score distribution in relation to its width [30].

Meanwhile, a Normal P-Plot can be used the examine the normality of error terms. The diagram compares the cumulative distribution of real data values with that of a normal distribution [12].The normal distribution creates a linear diagonal line for comparing the plotted residuals [12].The residual line closely follows the diagonal in a normal distribution [8]. Second, the linearity of the association between the dependent and the independent variable indicates the extent to which variation in the dependent variable is related to variation in the independent variable [12]. Such data can be checked graphically through scatter or partial regression plots [18].

Thirdly, homoscedasticity involves equality in error variance over the entire range of forecasted values. This test requires a scatter plot of standardized residuals against forecasted values [12]. This assumption can be confirmed by a scatter plot of SRESID versus ZPRED, which shows a constant linear relationship between them. Fourthly, multicollinearity expresses the relationship among three or more independent variables when an individual variable is regressed on others [12]. Multicollinearity arises due to high correlation among the independent variables, which leads to large standard errors and lowers the precision of estimated constant terms [13]. Multicollinearity can be measured using a Variance Inflation Factor (VIF). The VIF and tolerance values serve as standard diagnostics, with VIF values over 5 (others recommend 10) signalling significant risk [13].

The last assumption is the independence of residuals. This assumption requires that the residuals be independent, meaning the error terms are not autocorrelated. The independence of residuals is usually tested using the Durbin-Watson statistic. Failure to test this assumption renders the results of the generalised linear models invalid if the data are temporal or clustered [8]. The ideal range for the Durbin-Watson statistic is from 1.5 to 2.5, and a p-value greater than 0.05 signifies no autocorrelation.

3. Methodology

This research used a quantitative, cross-sectional design employing a survey approach. The target respondents consisted of permanent academic staff from Malaysian HEIs listed in the QS World Rankings 2023. A purposive sampling was employed to guarantee that participants fulfilled three criteria, which are Malaysian citizenship, permanent employment status, and currently working with one of the listed local institutions in QS World Ranking 2023, guaranteeing representation across research, comprehensive, focused, and private university classifications. In order to guarantee that the participants are relevant to the variables under study, these requirements are crucial. However, they might not be representative of the diverse community as a whole due to specific traits, making it harder to conclude the whole. The constructs encompassed PE, FWAs, POS, KS, TL, IIC, and IWB.

All of the items are examined using a five-point Likert scale, with 1 indicating strongly disagree and 5 indicating strongly agree. The questionnaire was sent electronically to participants from various faculties and academic levels. Around 389 questionnaires were received, and after the data cleaning, all 389 responses remained for analysis. Data were assessed using SPSS Version 29 to analyze the multivariate assumptions. Tests were specifically performed for multivariate normality, residual normality, linearity, homoscedasticity, multicollinearity and residual independence. Although SmartPLS 4.0 was used in the main investigation to evaluate the structural model, this paper focuses solely on assumption testing with SPSS. SPSS Version 29 was chosen expressly for multivariate assumption testing because of its well-known diagnostic capabilities for regression-based analyses, such as residual plots, normal probability plots, collinearity diagnostics, and the Durbin-Watson statistic. These processes lack comprehensive support in PLS-SEM software systems. Due to the methodological nature of this paper's focus on assumption verification rather than model estimation, thus, SPSS serves as a transparent and generally recognised platform for conducting and reporting assumption diagnostics prior to PLS-SEM analysis.

4. Results

There are two reasons why verifying assumptions is essential. Initially, distortions and biases may arise from the intricate structure of the connections derived from numerous inputs. Secondly, the intricate nature of the study and results may obscure the indicators of assumption violations that are evident in simpler univariate analyses [12]. The current paper examines the 6 key assumptions, which are multivariate normality, normality of error terms, linearity, homoscedasticity, multicollinearity and independence of residuals.

4.1 Multivariate Normality

As recommended by Hair *et al.,* [13] the normality of the data distribution was assessed using multivariate skewness and kurtosis. As SPSS cannot directly assess multivariate normality, this evaluation was performed using an online program available at: https://webpower.psychstat.org/models/kurtosis/. Mardia's test of skewness and kurtosis was performed using the WebPower online application [31] to evaluate multivariate normality. As presented in **Figure 1**, the results showed skewness (β = 31.06, p < .01) and kurtosis (β = 372.87, p < .01), indicating that the data were not multivariate normal. Both exceeded permissible standards (skewness > 3, kurtosis > 20).

```
Sample size:   389
Number of variables:   17

Univariate skewness and kurtosis
       Skewness SE_skew Z_skew Kurtosis SE_kurt Z_kurt
FWA      -0.675   0.124 -5.455    0.719   0.247  2.912
IC       -0.392   0.124 -3.165    0.334   0.247  1.351
IE       -0.302   0.124 -2.439    0.212   0.247  0.860
IG       -0.330   0.124 -2.670    0.163   0.247  0.659
II       -0.589   0.124 -4.757    0.356   0.247  1.444
IIC      -0.478   0.124 -3.863   -0.008   0.247 -0.031
IWB      -0.457   0.124 -3.691    0.325   0.247  1.315
KS       -0.445   0.124 -3.598    0.518   0.247  2.097
KS_C     -0.600   0.124 -4.847    0.387   0.247  1.568
KS_D     -0.489   0.124 -3.952    0.350   0.247  1.418
PE       -0.629   0.124 -5.081    0.223   0.247  0.904
PE_C     -0.833   0.124 -6.731    0.367   0.247  1.487
PE_IM    -0.404   0.124 -3.262   -0.161   0.247 -0.653
PE_M     -1.148   0.124 -9.279    0.518   0.247  2.100
PE_SD    -0.637   0.124 -5.147    0.282   0.247  1.144
POS      -0.427   0.124 -3.451    0.145   0.247  0.587
TL       -0.809   0.124 -6.535   -0.232   0.247 -0.939

Mardia's multivariate skewness and kurtosis
                  b         z p-value
Skewness   31.05792 2013.589       0
Kurtosis  372.86892   19.349       0
```

Fig. 1. Mardia's multivariate Skewness and Kurtosis

4.2 Normality of Error Term

The subsequent evaluation involved examining the normality of the error terms. The normality of the error term was evaluated by a Normal P-P Plot. As shown in **Figure 2**, the plot demonstrated that the error terms were closely aligned with the diagonal reference line, suggesting that the residuals were almost normally distributed. Despite the dataset's violation of multivariate normality as indicated by Mardia's test, the normal distribution of residuals substantiates the validity of the inferential statistics obtained from the regression model [8].

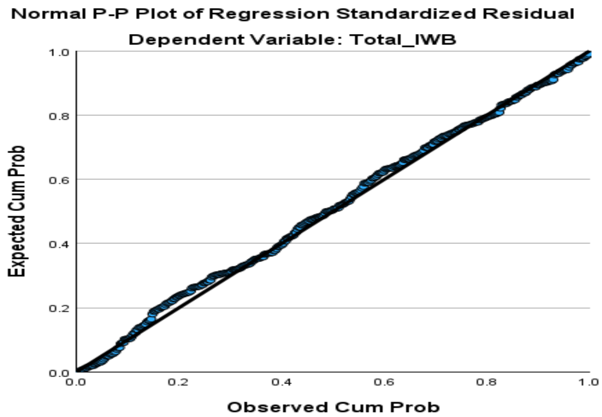

Fig. 2. P-P Plot of standardized residual

4.3 Linearity

The following multivariate assumption is to ensure that all the construct is normally distributed. Linearity was assessed by scatterplots of each independent variable against the dependent variable, in conjunction with a lot of all predictors versus the anticipated value. The plot showed a consistent linear pattern, indicating a linear relationship between the independent factors and the dependent variable (Total_IWB) as visualised in **Figure 3**. This visual pattern demonstrates that the assumption of linearity is fulfilled, hence validating the suitability of employing multiple regression analysis in this study [8]. **Fig. 3** demonstrates the model's overall linearity.

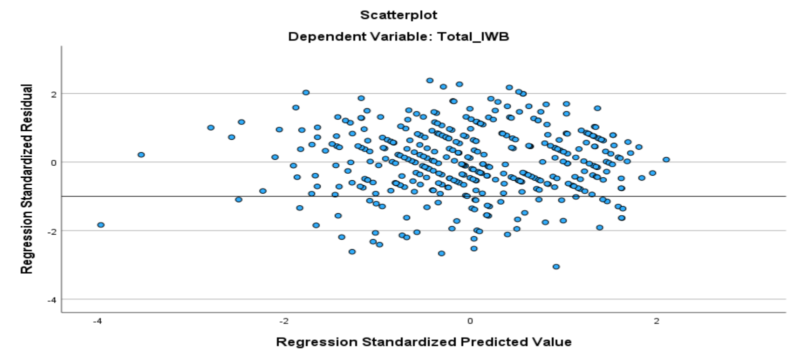

Fig. 3. Regression standardized residual vs regression predicted value

4.4 Homoscedasticity

Next, multivariate analysis continues with the assumption of constant variance, which checks for homoscedasticity in the data. Homoscedasticity was assessed by a scatterplot of standardized residual (SRESID) plotted against standardized predicted values (ZPRED). The scatterplot in **Figure 4** demonstrates a random pattern without funnel shapes or curvature, confirming the presence of constant variance. This validates the homoscedasticity assumption necessary for multiple regression analysis [8].

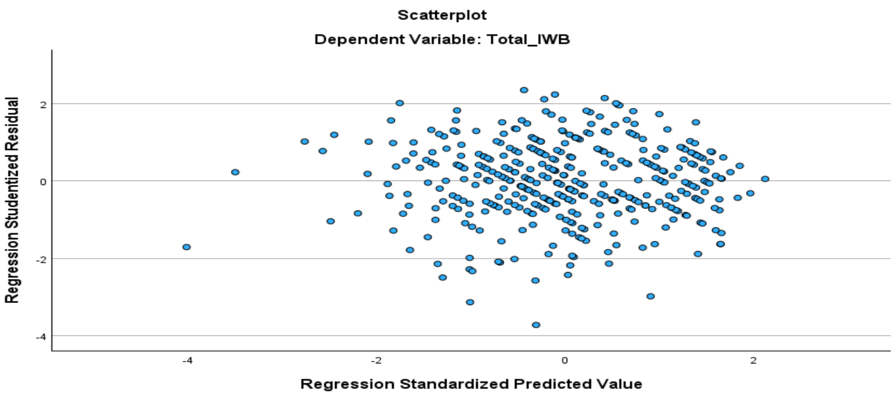

Fig. 4. Scatterplot regression studentized residual vs regression standardized predicted value

4.5 Multicollinearity

Multicollinearity was checked by observing the Tolerance and VIF values for all predictor variables in this regression model. The range of tolerance values was from 0.397 to 0.763, all above the conventional cutoff point of 0.10, indicating that predictors are distinct enough. Correspondingly, VIF values ranged from 1.311 to 2.518, staying well below the critical level of 3.3, thus indicating that the inflation of regression coefficients due to multicollinearity is not critical. These findings support the conclusion that problems of multicollinearity are not present, and independent variables provide unique information values to the model. Table 1 displays the collinearity statistics.

Table 1
Multicollinearity statistics

Construct	Collinearity Statistics	
	Tolerance	VIF
Total_PE	.495	2.020
Total_FWAs	.763	1.311
Total_POS	.530	1.886
Total_KS	.692	1.445
Total_TL	.537	1.861
Total_IIC	.459	2.180
Total_IWB	.397	2.518

a. Dependent Variable: Total_IWB

4.6 Independence of Residual

The final multivariate assumption tested in this research is autocorrelation. The independence of residuals was tested using the Durbin-Watson Statistic, which tests for autocorrelation in residuals from regression analysis. As shown in **Table 2**, it can be observed that the results showed a Durbin Watson Statistic of 1.989, which is well within the acceptable limit of 1.5 to 2.5 [8]. This signifies that the residuals exhibit no significant autocorrelation, hence fulfilling the assumption of independence. Satisfying the assumption of independence confirms that the residuals of the models are not correlated in terms of time or sequence and thus confirms the inferential statistics used in the regression analysis.

Table 2
Auto-correlation

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.776[a]	.603	.597	.35816	1.989
a. Predictors: (Constant), Total_IIC, Total_POS, Total_FWAS, Total_KS, Total_TL, Total_PE					
b. Dependent Variable: Total_IWB					

5. Discussion

This study intended to assess the fulfillment of multiple regression and PLS-SEM assumptions in examining drivers of IWB among academics in Malaysian HEIs. The findings demonstrate that the data met essential assumptions, including normality of error term, linearity, homoscedasticity, multicollinearity, and independence of residuals through visual plots and statistical diagnostics. Despite the dataset not satisfying the assumption of multivariate normality as indicated b's test (β_skewness = 31.06, $p < 0.01$; β_kurtosis = 372.87, $p < 0.01$), the normal P–P plot of regression scaled residuals demonstrated that the error terms were roughly normally distributed. Multivariate data often exhibits non-normality in social science research [4], additional analysis can be carried out because regression and PLS-SEM are resilient to such breaches, especially when the sample sizes are sufficient. Verifying these assumptions before model estimation enhances the validity and replicability of the findings [13].

Next, the assumption of linearity was also validated. The scatterplot of standardized residuals vs standardized predicted values exhibited a random distribution of data points without obvious curvature, indicating a linear relationship between the independent and dependent variables. This was also confirmed by separate scatterplots of each independent variable-dependent variable association, where linear trends were evident. Consequently, both individual and overall linearity assumptions were satisfied.

In regard to homoscedasticity, from the scatter plot, it can be determined that there is a uniform distribution of residuals for all levels of predicted values, meaning there are no funneling or clustering patterns observed. Therefore, it can be confirmed that the variance in residuals is constant, satisfying the assumption of homoscedasticity. The following is an analysis of multicollinearity. The multicollinearity examination presents that tolerance levels range from 0.397 to 0.763, while VIF levels range from 1.311 to 2.518, respectively. The outcome is well within acceptable ranges (Tolerance > 0.10, VIF < 3.3). Thus, there are no concerns about multicollinearity in respect to the regression model. This indicates that each predictor provides distinct explanatory value without overlap. Lastly, the Durbin-Watson Statistic, ranging from 1.989, does not show any significant autocorrelation of residuals, thus satisfying another assumption: error independence.

In summary, the diagnostic analyses demonstrate that the prescribed statistical assumptions are met for the regression analysis and PLS-SEM analyses. The results also exemplify strong research methodology by emphasizing diagnostic testing, frequently neglected in behavioural studies [26].. This enhances the validity of the assumptions used in the analysis of the determinants of IWB in the academic context. Furthermore, the high methodological quality used in the assumption testing provides the underpinning for the analysis of the relationships between the psychological, organizational, and behavioural elements of the context of the higher education system in Malaysia.

6. Conclusion

This study investigated the validity of essential multivariate assumptions underlying regression and PLS-SEM analyses involving IWB among academics in Malaysian HEIs. It was observed that, with the exception of non-violation of multivariate normality, other assumptions such as residual normality, linearity, homoscedasticity, multicollinearity, and residual independence were sufficiently met. The findings justify the appropriateness of using both multiple regression and PLS-SEM for data analysis in this study. The current findings also highlight the relevance of testing assumptions as a vital preliminary step in quantitative research. Moreover, assumption testing enhances the clarity of the methodology and provides a reference for future researchers to apply similar parametric statistical approaches.

7. Implication and Limitation

The main implication of the current study is methodological. By implementing strict assumption testing, regression and SEM results can be more valid and accurate. This becomes particularly important in settings where survey data and complex models are the norm. Validation of these assumptions provides a sound base upon which the associations among psychological, organizational, and behavioral factors relevant to IWB can be analyzed. From a practical viewpoint, institutions interested in encouraging faculty innovation may employ established approaches for evidence-based decision-making and policy development. Future research is encouraged to replicate this diagnostic approach across multiple industries and to explore longitudinal designs that allow insights into causal relations over time.

In spite of the contributions of this research with respect to the methodologies employed, it does have some limitations. First, the breach of multivariate normality may restrict the generalizability of results from approaches that predominantly depend on this assumption, such as covariance-based structural equation modeling (SEM). However, the use of the PLS-SEM technique mitigates this problem. Second, the assumption checks relied on visual inspections and diagnostic statistics from SPSS, which, although widely recognized, may occasionally be subjective. Third, the study exclusively examined academics from Malaysian HEIs, thereby limiting the generalizability of the findings to other professional or cultural settings. Finally, the data employed were cross-sectional, inhibiting the ability to infer causal relationships.

8. Future Research and Directions

Future studies can enhance the current framework of methodologies by integrating similar assumption-testing methodologies into the design of longitudinal data, which would improve the process of making causal statements. In addition to that, a comparison study of other industries may lead to the identification of systematic differences of assumption violations among contexts. The enhancement of assumption test approaches can also be assessed using robust estimation procedures. Such efforts would enhance methodological rigour in behavioural and innovation research.

References

[1] Ardianti, Tanti, Martinus Tukiran, and Diah Mariana. "Innovative work behavior in higher education: A systematic literature review." *Research and Development Journal of Education* 10, no. 2 (2024): 975-985. https://doi.org/10.30998/rdje.v10i2.23807

[2] Asurakkody, Thanuja Ariyasinghe, and Sang Hee Kim. "Effects of knowledge sharing behavior on innovative work behavior among nursing Students: Mediating role of Self-leadership." *International Journal of Africa Nursing Sciences* 12 (2020): 100190. https://doi.org/10.1016/j.ijans.2020.100190

[3] Berber, N. (2024). *Job Satisfaction, Flexible Work Arrangements and Innovative Work Behavior in Serbian SMEs*. *January 2025*. https://doi.org/10.24867/IJIEM-368

[4] Cain, Meghan K., Zhiyong Zhang, and Ke-Hai Yuan. "Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation." *Behavior research methods* 49, no. 5 (2017): 1716-1735. https://doi.org/10.3758/s13428-016-0814-1

[5] Chen, Chaorong, and Anan Pongtornkulpanich. "Motivation, knowledge sharing, and innovative work behaviors of university teachers." *Journal of System and Management Sciences* 14, no. 4 (2024): 86-104. https://doi.org/10.33168/JSMS.2024.0406

[6] Ebrahim, Z. B., Ismail, I., & Kassim, E. S. (2025). Role of Transformational Leadership And Perceived Organizational Support in Promoting Innovation Among Malaysian Academics. *International Journal of Accounting, Finance and Business*, *10*(59), 369–385.

[7] Eisenberger, Robert, Robin Huntington, Steven Hutchison, and Debora Sowa. "Perceived organizational support." *Journal of Applied psychology* 71, no. 3 (1986): 500. https://doi.org/10.4337/9781803921761.00095

[8] Field, A. P. (2018). *Discovering Statistics Using IBM SPSS Statistics* (5th ed.). SAGE Publications Inc.

[9] Genari, Denise, Kadigia Faccin, and Bruno Anicet Bittencourt. "What makes an individual more innovative? A systematic review on individual innovation competencies." *International Journal of Innovation Management* 28, no. 05n06 (2024): 2450021. https://doi.org/10.1142/S136391962450021X

[10] Ghimire, Binod, Rewan Kumar Dahal, and Bharat Rai. "The attitude of flexible work arrangement on academics' job satisfaction: The emerging market case." *Journal of System and Management Sciences* 13, no. 2 (2023): 370-383. https://doi.org/10.33168/JSMS.2023.0226

[11] Grošelj, Matej, Matej Černe, Sandra Penger, and Barbara Grah. "Authentic and transformational leadership and innovative work behaviour: the moderating role of psychological empowerment." *European Journal of Innovation Management* 24, no. 3 (2021): 677-706. https://doi.org/10.1108/EJIM-10-2019-0294

[12] Hair, Joseph F., William C. Black, Barry J. Babin, and Rolph E. Anderson. "Multivariate data analysis." (2019).

[13] Hair, Joseph Franklin, Hult, G. T. M., Ringle, C. M., & Marko Sarstedt. (2022). *A Primer On Partial Least Squares Structural Equation Modeling (PLS-SEM)*. SAGE Publications Inc. https://doi.org/10.1007/978-3-030-80519-7

[14] Ismail, Irzan, Zarina Begum Ebrahim, Erne Suzila Kassim, and Bandar Puncak Alam Alam. "How individual factors shape innovative work behavior in malaysian heis: the role of innovation capability, knowledge sharing and psychological empowerment." *Information Management and Business Review* 16, no. 3 (2024): 495-513. https://doi.org/10.22610/imbr.v16i3(I)S.4077

[15] Janssen, Onne. "Job demands, perceptions of effort-reward fairness and innovative work behaviour." *Journal of Occupational and organizational psychology* 73, no. 3 (2000): 287-302. https://doi.org/10.1348/096317900167038

[16] Joe F. Hair, J., Page, M., & Brunsveld, N. (2020). *Essentials of Business Research Methods* (4th Editio). Routledge. https://doi.org/10.4324/9781315704562

[17] Joseph F. Hair, J., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd Editio). SAGE Publications Inc.

[18] Keith, T. Z. (2019). *Multiple Regression and Beyond: An Introduction to Multiple Regression and Structural Equation Modeling* (3rd ed.). Routledge. https://doi.org/10.4324/9781315162348

[19] Kim, Juhee, Agyemang Amofa Prempeh, Emmanuel Kyeremeh Addai, and Elizabeth Wargo. "The effect of knowledge sharing on innovative work behaviour at higher education institutions." *Higher Education Quarterly* 79, no. 1 (2025): e12574. https://doi.org/10.1111/hequ.12574

[20] Kline, R. B. (2016). Principles and Practice of Structural Equation Modeling. In *Canadian Graduate Journal of Sociology and Criminology* (4th ed., Vol. 1). The Guilford Press. https://doi.org/10.15353/cgjsc.v1i1.3787

[21] Lei, Hui, Lathong Leaungkhamma, and Phong Ba Le. "How transformational leadership facilitates innovation capability: the mediating role of employees' psychological capital." *Leadership & Organization Development Journal* 41, no. 4 (2020): 481-499. https://doi.org/10.1108/LODJ-06-2019-0245

[22] Lin, Qingjin. "Transformational leadership and innovative work behavior: The role of identification, voice and innovation climate." *International Journal of Hospitality Management* 113 (2023): 103521.

[23] Mirzaee, Somayyeh, and Ali Ghaffari. "Investigating the impact of information systems on knowledge sharing." *Journal of Knowledge Management* 22, no. 3 (2018): 501-520. https://doi.org/10.1108/JKM-08-2017-0371

[24] Muchiri, Michael K., Adela J. McMurray, Mathews Nkhoma, and Hiep C. Pham. "Mapping antecedents of innovative work behavior: A conceptual review." *The Journal of Developing Areas* 54, no. 4 (2020). https://doi.org/10.1353/jda.2020.0047

[25] Nugroho, Riyadi. "Knowledge sharing as key driver for the rise of innovative work behavior." *Media Ekonomi dan Manajemen* 38, no. 2 (2023): 266-284. https://doi.org/10.56444/mem.v38i2.3513

[26] Osborne, Jason W., and Elaine Waters. "Four assumptions of multiple regression that researchers should always test." *Practical assessment, research, and evaluation* 8, no. 1 (2002). https://doi.org/https://doi.org/10.7275/r222-hv23

[27] Saif, Naveed, Gerald Guan Gan Goh, Abner Rubin, Imrab Shaheen, and Muhammad Murtaza. "Influence of transformational leadership on innovative work behavior and task performance of individuals: The mediating role of knowledge sharing." *Heliyon* 10, no. 11 (2024). https://doi.org/10.1016/j.heliyon.2024.e32280

[28] Spreitzer, Gretchen M. "Psychological empowerment in the workplace: Dimensions, measurement, and validation." *Academy of management Journal* 38, no. 5 (1995): 1442-1465. https://doi.org/10.1007/978-1-4471-4953-8_17

[29] Tabachnick, B. G. (2019). *Using Multivariate Statistics* (7th ed.). Pearson.

[30] Watkins, Marley W. "Exploratory factor analysis: A guide to best practice." *Journal of black psychology* 44, no. 3 (2018): 219-246. https://doi.org/10.1177/0095798418771807

[31] Zhang, Z., and K. H. Yuan. *Practical Statistical Power Analysis Using Webpower and R(Eds). Granger, IN: ISDSA Press*. 2018. https://doi.org/10.35566/power