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The Work Environment as an Intervening Variable Between Compensation and Work Facilities on Job Satisfaction at PT Telkom Akses Balikpapan

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ABSTRACT

The study employs a quantitative approach using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) method. The research sample consists of 59 employees of PT Telkom Akses Balikpapan, selected through a census sampling method. Data were collected through the distribution of structured questionnaires. The results reveal that compensation has a significant impact on the work environment, and work facilities also significantly influence it. A conducive work environment contributes significantly to job satisfaction. However, compensation has a direct but insignificant effect on job satisfaction, while work facilities have a significant direct impact. Furthermore, the work environment fully mediates the relationship between compensation and job satisfaction and partially mediates the relationship between work facilities and job satisfaction. The study concludes that the work environment plays a crucial mediating role in enhancing employee job satisfaction, particularly by optimizing the effects of compensation and work facilities. Improving the quality of the work environment is essential in addressing job satisfaction issues at PT Telkom Akses Balikpapan.

1. INTRODUCTION

Compensation has an evident influence on job satisfaction. Research by Amalia et al. (2024) suggests that compensation plays a significant role in employee job satisfaction, with the analysis revealing a positive correlation between compensation variables and job satisfaction. Furthermore, work facilities also play an essential role in creating a positive effect on employee job satisfaction, emphasizing the importance of a supportive physical environment to increase productivity (Prawira, 2020). In addition to compensation and work facilities, the overall work environment plays an essential role in influencing job satisfaction. Rasyid and Tanjung (2020) noted that both physical and non-physical work environments, including organizational culture and interaction between colleagues, are factors that should not be ignored.

PT Telkom Akses Balikpapan, as one of the companies engaged in telecommunication infrastructure, faces challenges in maintaining employee job satisfaction. Therefore, this study is entitled The Work Environment as an Intervening Variable Between Compensation and Work Facilities on Job Satisfaction at PT Telkom Akses Balikpapan. This study aims to analyze the influence of compensation, work facilities, and work environment on employee job satisfaction at PT Telkom Akses Balikpapan. By understanding the factors that contribute to job satisfaction, companies can design more effective strategies to improve employee well-being and work productivity.

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Some previous studies related to this study include those by Fajar and Maria (2022), which show that the work environment, along with discipline and compensation, has a significant impact on employee performance at PT Virtus Facilities Services. Data obtained through multiple linear regression models indicate that a conducive work environment enhances performance, which in turn affects employee job satisfaction.

The study by Kurniawan et al. (2023) examines the impact of a toxic work environment on employee performance in the food and beverage sector. The study found that a hostile work environment can lower performance, potentially reducing job satisfaction through mediators such as employee engagement and work stress. Research by Fortuna & Nugroho (2024) states that the workplace has a positive but insignificant impact on the work environment, while work pressure has a negative impact on the implementation of representation (Fortuna & Nugroho, 2024). A study by Jami et al. found that motivation acts as a mediator between the work environment and employee performance. A good environment increases satisfaction through increased motivation (Jami et al., 2022).

Memon et al. (2021) emphasize the importance of effective human resource management practices in promoting high work engagement, which in turn affects employee satisfaction and retention. A positive work environment has a significant impact on the relationship between management practices and employee satisfaction. Research by Fadilah et al. (2023) suggests that training and the work environment affect employee performance, with job satisfaction acting as a moderating variable. The findings suggest that a good work environment and adequate training support are crucial for enhancing job satisfaction and effectiveness. Haeruddin et al. (2022) focus on the adverse effects of a toxic work environment and its impact on employee exit intentions and overall satisfaction. Findings suggest that a hostile work environment is associated with lower job satisfaction and increased intention to exit. At PT Inti Dufree Promosindo, Kresmawan et al. (2021) found that the work environment has a significant positive influence on performance. This suggests that attention to both the physical and psychological aspects of the environment in compensation policies is crucial for enhancing job satisfaction. The explanation from Zhenjing et al. (2022) provides insight into the understanding that the work environment has a direct effect not only on performance but can also mediate the relationship between other factors, such as compensation and workplace policies, and job satisfaction.

Previous studies have examined factors that affect employee job satisfaction, including compensation, work facilities, and work environment. Fajar and Maria (2022) demonstrate that the work environment, along with discipline and compensation, has a significant impact on employee performance, which ultimately affects job satisfaction. However, some other studies highlight that the work environment can also have a negative impact on employee performance and satisfaction. Kurniawan et al. (2023) found that a toxic work environment can degrade performance and reduce job satisfaction, primarily through work stress mechanisms and low employee engagement. Haeruddin et al. (2022) also show that a hostile work environment can increase employee exit intention, thereby reducing job satisfaction levels. Meanwhile, research by Zhenjing et al. (2022) revealed that the work environment not only has a direct effect on performance but can also mediate the relationship between other factors, such as compensation and workplace policies, on job satisfaction.

Although previous research has addressed the relationship between work environment, compensation, and job satisfaction, there are still some research gaps that have not been widely explored. First, most studies focus more on the direct relationship between compensation, work facilities, and job satisfaction without considering the work environment as a mediating variable. Studies such as those conducted by Memon et al. (2021) and Wirastini & Sariani (2024) demonstrate that compensation and work facilities can enhance job satisfaction; however, they have not investigated whether the work environment serves as a mediator in these relationships. Second, many previous studies have focused more on specific industry sectors, such as banking, food and beverages, and retail. At the same time, there has been no research that examines this phenomenon explicitly in the telecommunications industry, particularly at PT Telkom Akses Balikpapan. This study aims to fill this gap by making the work environment an intervening variable in the relationship between compensation, work facilities, and employee job satisfaction.

2. RESEARCH METHOD

This study employs a quantitative approach, utilizing a survey method. The research model used is a path analysis method based on Partial Least Squares Structural Equation Modeling (PLS-SEM). The research was conducted from March to April 2023. In this study, the population consists of all 59 employees working at the PT Telkom Akses office in Balikpapan. The census sampling technique, which involves including every individual within the population in the study, enables a comprehensive analysis of the workforce. This approach is particularly relevant in contexts where the number of individuals is manageable, ensuring maximum participation and reducing potential sampling bias inherent in other methods, such as random sampling or stratified sampling (Putra et al., 2023). By utilizing the entire employee base, researchers can gain deeper insights into the various dynamics that affect employee performance and organizational behavior.

In this research, conducted at PT Telkom Akses Balikpapan, data were collected using a well-structured questionnaire based on indicators derived from relevant research variables. The questionnaire was formulated using a 5-point Likert scale to measure respondents' perceptions of the variables studied. This choice of methodology is supported by various sources in the existing literature that emphasize the suitability and reliability of the Likert scale in measuring attitudes and perceptions. The 5-point Likert scale is widely recognized for its effectiveness in measuring an individual's level of agreement or disagreement with specific statements related to the variables being studied. This scale provides a nuanced measurement that allows respondents to express varying degrees of opinion, thereby enriching the data collected. The 5-point format is easy to understand, even for younger respondents, indicating its versatility across demographics (Lee et al., 2020). Further research confirms that the scale allows for precise quantification of subjective responses, improving data quality in a variety of contexts, including educational assessments and organizational studies (Sim et al., 2021; Rabiu et al., 2023).

The evaluation of measurement and structural models is a crucial aspect of research methodology, particularly when ensuring that instruments effectively measure the variables of interest. This process involves a rigorous assessment of validity and reliability in the measurement model, followed by an evaluation of the structural model that tests the relationships between these variables. To begin with, evaluating the measurement model is essential for determining whether the constructs within a study accurately reflect the theoretical concepts they aim to measure. Validity assesses whether an instrument measures what it is supposed to measure, while reliability concerns the consistency of the measurement over time. In the context of educational evaluations, tools such as the Rasch Measurement Model (RMM) are often used to establish the reliability and validity of measurement tools. Roberts et al. demonstrated the effectiveness of the Rasch Measurement Model in evaluating the English Language Textbook, highlighting its role in establishing the reliability and validity of educational resources (Roberts et al., 2022). Furthermore, similar methodologies are adopted in various fields, emphasizing the importance of a strong empirical basis for constructs being evaluated in research endeavors (Shahid et al., 2022).

The analytical steps to evaluate the measurement model are essential to ensure that the instrument used is valid and reliable. The first step in this process is evaluating the Measurement Model. This involves conducting validity and reliability tests to ensure that the instrument accurately measures the desired variables. According to Goretzko et al., confirming model fit in a measurement model, particularly through Confirmatory Factor Analysis (CFA), requires careful consideration and sometimes adaptation of the fit indices used to assess the model (Goretzko et al., 2024). They emphasize the importance of not relying on fixed thresholds, as different datasets may require varying thresholds for an acceptable fit, indicating a nuanced understanding of the instrument's reliability and validity.

Furthermore, the Rasch measurement model has shown significant advantages in evaluating the reliability and validity of educational instruments. It facilitates the effective linking of pre- and post-test results to item difficulty levels (Alatas et al., 2024). Similarly, a study by Laliyo et al. (2022) confirmed the usefulness of the Rasch Measurement Model to measure changes in conceptual understanding in educational settings, demonstrating its application for reliability assessment. In addition, Agustina et al. emphasized the need to establish the

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validity and reliability of the assessment tool to ensure that it accurately measures competencies related to critical thinking skills (Agustina et al., 2023).

The second phase, Structural Model Evaluation, aims to test the causal relationships between variables through path coefficients and R-squared values. A robust structural model should show clear relationships between variables while explaining a significant amount of variance in the dependent variable. Mirete et al. highlighted the importance of structural equation models in the educational context, stating that they allow the analysis of relationships between latent and observed variables. Their study emphasized that the development of causal structural models is based on established theory and previous research, which ensures that the causal relationships articulated in the model have theoretical validity (Mirete et al., 2020). This empirical foundation is essential for establishing the reliability of the path coefficients and R-squared values obtained from the model.

Hypothesis testing is the third and crucial step in this analysis, utilizing t-statistics and p-values to ascertain the significance of the relationships in the model. By using these statistical measures, researchers can determine which paths in the structural equation are statistically significant, providing a deeper understanding of the relationships between variables. The evaluation mentioned by Zhao et al. on modeling uncertainty in measurement underscores the importance of rigorous quantitative methods in testing hypotheses in various contexts (Zhao et al., 2022).

3. RESULTS AND DISCUSSIONS

The results obtained after calculating the PLS-SEM Algorithm and making corrections to various parameters yielded the final model structure, as shown in Figure 1. In the figure, several indicators show reductions due to a lack of value provisions.

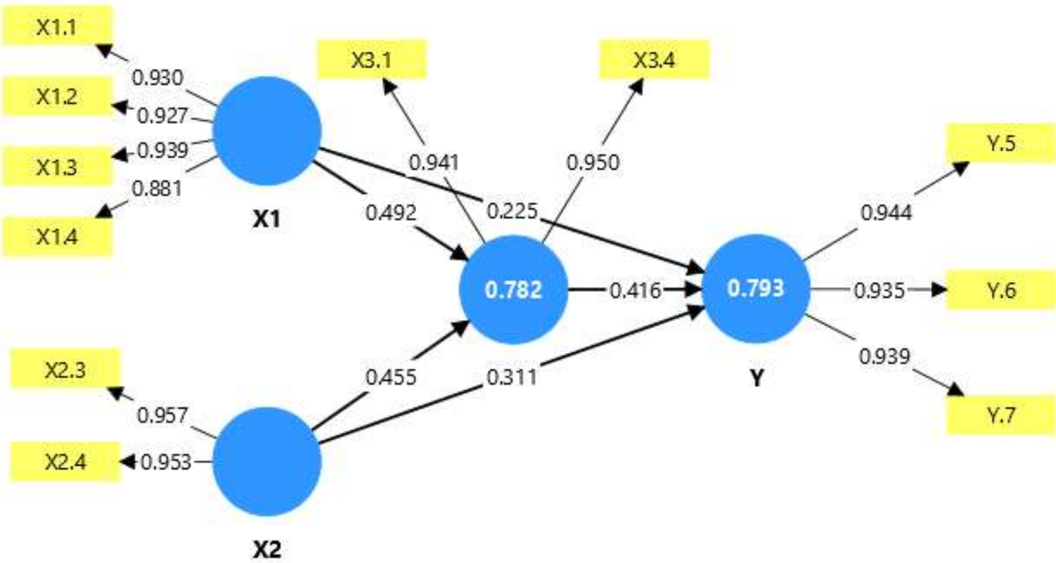

Fig 1. Final Model Structure

Description:
X1=Compensation, X1.1=Salary, X1.2=Incentive, X1.3=Allowances, X1.4=Compensation Facility
X2=Work Facilities, X2.1=Office Facilities, X2.2=Work Supplies, X2.3=Parking Facilities, X2.4=Office Space, X2.5=Operational Vehicles
X3=Work Environment, X3.1=Working Atmosphere, X3.2=Social Relations, X3.3=Office Supplies, X3.4=Peer Support, X3.5=Leadership Supervision
Y=Job Satisfaction, Y1=Job Responsiblities, Y2=Supervisor’s Attention, Y3=Employee Well-Being
Y4=Innovation Opportunities, Y5=Salary Suitability Fan Allowance, Y6=Peer Support, Y7=Comfort of The Environment

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Outer Loadings are a measure that indicates the extent to which an indicator can represent latent variables in a Structural Equation Modeling (SEM) model based on Partial Least Squares (PLS). An Outer Loadings value greater than 0.7 indicates that the indicator has a substantial contribution to the latent variable and is worth maintaining. Meanwhile, values between 0.4 and 0.7 can still be considered to be maintained if the Average Variance Extracted (AVE) and Composite Reliability (CR) remain in compliance with the established criteria. Outer Loadings play an essential role in assessing the validity of convergences, ensuring the reliability of indicators, and determining the feasibility of indicators in research models (Zazilah et al., 2023). Table 1 presents the values of the outer loadings, all of which are greater than 0.7.

Table 1. Outer Loadings-Matrix

	X_1	X_2	X_3	Y
$X_{1.1}$	0,930			
$X_{1.2}$	0,927			
$X_{1.3}$	0,939			
$X_{1.4}$	0,881			
$X_{2.3}$		0,957		
$X_{2.4}$		0,953		
$X_{3.1}$			0,941	
$X_{3.4}$			0,950	
Y_5				0,944
Y_6				0,935
Y_7				0,939

Source: data processed, 2025

Table 2. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	Average variance extracted
X_1	0,939	0,940	0,956	0,845
X_2	0,903	0,904	0,954	0,912
X_3	0,883	0,887	0,944	0,895
Y	0,933	0,933	0,957	0,882

Source: data processed, 2025

Construct Reliability and Validity are measurements in Structural Equation Modeling (SEM) that ensure a construct or latent variable is measured consistently and accurately through the indicators used. Reliability refers to the extent to which a construct provides consistent results, which can be calculated using Cronbach's Alpha and Composite Reliability (CR), with an ideal value of ≥ 0.7 to indicate good reliability. Meanwhile, validity ensures that the indicators in the model measure the construct in question.

There are two main types of validity, namely convergent validity which is assessed through Average Variance Extracted (AVE) with a minimum value of 0.5, and discriminant validity which aims to ensure that a construct does not have an excessive correlation with other constructs, which can be tested using the Fornell-Larcker Criterion or Heterotrait-Monotrait Ratio (HTMT) method (Pahmi et al., 2024; Haji-Othman & Yusuff, 2022). Construct Reliability and Validity Results as per Table 2. The values of all Cronbach's alphas and composite reliability are above 0.7, and the AVE is above 0.5. Discriminant validity is a test in Structural Equation Modeling (SEM) that ensures that a construct has a clear difference from other constructs in the research model. Two standard methods for assessing discriminant validity are the Fornell-Larcker Criterion and Cross Loadings. The Fornell-Larcker criterion compares the square root of the Average Variance Extracted (AVE) of each construct with the correlation between constructs.

Table 3. Discriminant Validity – Fornell-Larcker Criterion

	X_1	X_2	X_3	Y
$X_{1.1}$	0,930	0,675	0,770	0,761
$X_{1.2}$	0,927	0,694	0,762	0,747
$X_{1.3}$	0,939	0,711	0,770	0,763
$X_{1.4}$	0,881	0,659	0,752	0,677
$X_{2.3}$	0,668	0,957	0,804	0,794
$X_{2.4}$	0,756	0,953	0,763	0,772
$X_{3.1}$	0,728	0,718	0,941	0,806
$X_{3.4}$	0,839	0,831	0,950	0,817
Y_5	0,801	0,784	0,797	0,944
Y_6	0,729	0,801	0,817	0,935
Y_7	0,729	0,725	0,804	0,939

Source: data processed, 2025

Table 4. Discriminant Validity – Cross Loadings

	X_1	X_2	X_3	Y
X_1	0,930			
X_2	0,927	0,955		
X_3	0,939	0,821	0,946	
Y	0,881	0,820	0,858	0,939

Source: data processed, 2025

Table 5. Model Fit

	Saturated model	Estimated model
SRMR	0,042	0,042
d_ULS	0,119	0,119
d_G	0,293	0,293
Chi-square	103,661	103,661
NFI	0,864	0,864

Source: data processed, 2025

Discriminant validity is considered adequate if the square root of AVE of a construct is greater than the correlation between that construct and other constructs. This indicates that the construct is more effective in explaining the variance of its indicators than the variance it shares with different constructs. Cross-loadings evaluate the validity of the discriminator by comparing the correlation between the indicator and its construct with the correlation of that indicator against other constructs. Indicators are discriminantally valid if they have a higher load on the construct they measure compared to loading on other constructs (Zazilah et al., 2023). In Table 3. It can be seen that the value of each construct is greater than the correlation between the construct and the other constructs, in Table 4. It can be seen that the loading is higher for the construct being measured compared to the loading for other constructs.

The fit model in Partial Least Squares Structural Equation Modeling (PLS-SEM) refers to the evaluation of the extent to which the developed model matches the empirical data collected. Model fit assessment is critical to ensure that it accurately and reliably represents the relationships between variables. Some of the indices commonly used in PLS-SEM to assess fit models include the Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). SRMR measures the average difference between the observed correlation matrix and the one predicted by the model, with a value of less than 0.08 indicating a good model fit. Meanwhile, the NFI compares the tested model with the baseline model, where a value close to 1 indicates a good model (Saputra et al., 2025; Ul Haq et al., 2024; Narimawati et al., 2022). In Table 5, the SRMR value is less than 0.08, and the NFI value is close to 1, which means that this model is also a good fit.

The Variance Inflation Factor (VIF) is a measure used in regression analysis to assess the degree of multicollinearity among independent variables. VIF measures the extent to which the estimated variance of the regression coefficient increases due to the correlation between independent variables. High VIF values indicate the presence of significant multicollinearity, which can affect the reliability and interpretation of regression models. In general, a VIF value above 10 is considered to indicate high multicollinearity, while a value between 5 and 10 indicates a potential problem that requires further attention (Ul Haq et al., 2024). In Table 6, it can be seen that all VIF values are less than 5, so this model is safe from multicollinearity.

Table 6. Collinearity Statistics (VIF)

	X_1	X_2	X_3	Y
X_1			2,246	3,352
X_2			2,246	3,193
X_3				4,578

Source: data processed, 2025

Table 7. R-square

	R-square	R-square adjusted
X_3	0,782	0,774
Y	0,793	0,782

Source: data processed, 2025

Table 8. Path Coefficients

	X_1	X_2	X_3	Y
X_1			0,492	0,225
X_2			0,455	0,311
X_3				0,416

Source: data processed, 2025

Table 11. F-Square

	X_1	X_2	X_3	Y
X_1			0,493	0,073
X_2				0,147
X_3			0,422	
Y				0,182

Source: data processed, 2025

The R-squared, or coefficient of determination, is a measure that indicates the proportion of variance in a dependent variable that can be explained by an independent variable in a regression model. The value of R-squared ranges from 0 to 1; a value close to 1 indicates that the model can account for most of the variability in the dependent variable, while a value close to 0 indicates the opposite. The value of R-squared will be Substantial if ≥ 0.67 (Muriyatmoko, 2018; Agustina & Sukwika, 2021; Amin et al., 2022). Based on Table 7. It is known that the R-squared for X3 is 0.774, or 77.4 percent, while the R-squared for Y is 0.782, or 78.2 percent. Therefore, both can be considered substantial.

Path Coefficients are values that show the direction and strength of relationships between variables in path analysis. Path analysis is an extension of the multiple regression technique used to evaluate causal models by examining relationships between a set of variables. The path coefficient is obtained from the standard regression coefficient and is used to calculate the direct, indirect, and total effects in the model. In the context of Structural Equation Modeling (SEM), path coefficients help in understanding the extent to which independent variables affect dependent variables, either directly or through mediator variables. The value of this coefficient ranges from -1 to 1; A positive value indicates a unidirectional relationship, while a negative value indicates an opposite relationship. The closer the absolute value of 1, the stronger the relationship between these variables. In Table 8, it is evident that all values are positive, indicating a one-way relationship between all variables in this study.

The P-value in Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to test the statistical significance of the path coefficients in the model. The value of p indicates the probability that the observed outcome occurred by chance. In the context of PLS-SEM, p-values are typically obtained through a bootstrapping procedure, a resampling technique that generates an empirical sample distribution to estimate the significance of model parameters. By bootstrapping, researchers can get confidence intervals and test hypotheses related to path coefficients without assuming a specific distribution (Hair & Alamer, 2022).

The interpretation of the p-value in PLS-SEM, i.e., the P-value < 0.05, indicates that the relationship between the variables is statistically significant at a significance level of 5%, so that the null hypothesis can be rejected. A P-value ≥ 0.05 indicates that the relationship between variables is not statistically significant at a 5% significance level, so there is insufficient evidence to reject the null hypothesis. In Table 9, all P values < 0.05, which means the relationship between the variables is significant, except X1 against Y, where the P value > 0.05, which means the relationship between the two is not essential. The structural equations formed are as follows:

Equation of the 1st sub-structure:
X3 = b1.X1 + b2.X2 + e
= 0,492.X1 + 0,455.X2

Equation of the 2nd substructure :
Y = b1.X1 + b2.X2 + b3.X3 + e
= 0,225.X1 + 0,311.X2 + 0,416.X3

Table 9. Path Coefficients Bootstrapping

	Original sample (O)	**Sample mean (M)**	**Standard deviation**	**t-Statistics**	**p-Values**
X_1->X_3	0,492	0,493	0,105	4,658	0,000
X_1->Y	0,225	0,218	0,122	1,846	0,065
X_2->X_3	0,455	0,453	0,103	4,420	0,000
X_2->Y	0,311	0,322	0,102	3,059	0,002
X_3->Y	0,416	0,414	0,132	3,138	0,002

Source: data processed, 2025

In Table 10, it can be seen that the indirect relationship from X1 to Y through X3, or X2 to Y through X3, all P values are < 0.05, which means that the relationship is all significant.

Table 10. Specific Indirect Effects Bootstrap

	Original sample (O)	**Sample mean (M)**	**Standard deviation**	**t-Statistics**	**p-Values**
X_1->X_3->Y	0,204	0,207	0,086	2,371	0,018
X_2->X_3->Y	0,189	0,185	0,067	2,805	0,005

Source: data processed, 2025

Based on the results obtained from the Path Coefficients Bootstrapping, X1 has no significant effect on Y. However, in the Specific Indirect Effects Bootstrapping, X1 has a substantial impact on Y through X3, indicating that X3 is a partial mediator of X1's effect on Y. In the Path Bootstrap Rapping Coefficients, X2 has a significant impact on Y, and in the Specific Indirect Effects Bootstrap Rapping, X2 has a substantial effect on Y through X3. It can be said that X3 partially mediates the effect of X2 on Y. The evaluation of structural models in PLS-

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SEM encompasses a range of criteria, including f-squared, which is utilized to assess effect sizes in the analysis of relationships between latent variables (Mastur et al., 2023). Common criteria for evaluating F-Square are 0.02 (small), 0.15 (medium), and 0.35 (large), which indicate the extent to which independent variables contribute to the increase in the variance of the dependent variable. In Table 11, the correlation coefficient between X1 and X3 is 0.493, indicating a strong positive correlation. The relationship between X1 and Y is 0.073, indicating a slight correlation. The correlation between X2 and X3 is 0.422, also indicating a strong correlation. The correlation between X2 and Y is 0.147, indicating a medium correlation. The correlation between X3 and Y is 0.182, also indicating a medium correlation.

The study found that both compensation and work facilities have a significant influence on the work environment. Fair compensation that aligns with workload improves employees' perception of their surroundings, while adequate facilities, such as comfortable workspaces and proper equipment, foster a more positive and conducive environment. These findings align with those of Zhenjing et al. (2022), who emphasize the mediating role of the work environment, and with Fortuna and Nugroho (2024), who highlight the importance of workplace design despite its varying levels of impact. In turn, the work environment has a strong, positive effect on job satisfaction, supporting the view of Jami et al. (2022) that motivation and satisfaction are enhanced in a supportive setting. While direct effects of compensation on satisfaction are not significant—contrasting with Kresmawan et al. (2021)—work facilities do show a direct influence, echoing Fajar and Maria's (2022) findings. Notably, compensation and facilities both indirectly impact job satisfaction through the work environment. Mediation tests, including the Sobel test, confirm that the work environment is a significant intervening variable. The model's R-squared value indicates a strong explanatory power, and the model fit analysis supports the reliability of these findings in the context of PT, Back to Basics.

4. CONCLUSION

The research findings reveal that the work environment is not only significantly influenced by compensation and work facilities but also serves as a key factor in enhancing job satisfaction. Although compensation does not directly impact job satisfaction, the work environment fully mediates this relationship. Meanwhile, work facilities have a direct effect on job satisfaction, with the work environment acting as a partial mediator. Therefore, efforts to improve employee satisfaction at PT. Telkom Akses Balikpapan must include optimizing compensation and facilities, as well as fostering a supportive work environment.

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