JPPIPA 12(11) (2026)

Jurnal Penelitian Pendidikan IPA

http://jppipa.unram.ac.id/index.php/jppipa/index

The Effectiveness of OBE Learning Implementation in Improving Initial Competencies and Learning Outcomes of New Students

Arina Luthfini Lubis[1*], Frangky Silitonga[2]

[1] Room Division Management Study Program, Politeknik Pariwisata Batam, Batam, Indonesia.
[2] Cullinary Management Study Program, Politeknik Pariwisata Batam, Batam, Indonesia.

Received: December 11, 2025
Revised: October 21, 2026
Accepted: November 17, 2026
Published: November 30, 2026

Corresponding Author:
Arina Luthfini Lubis
a.luthfinilubis@gmail.com

DOI: 10.29303/jppipa.v12i11.13829

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Abstract: Problem: Evidence on how perceived Outcome-Based Education (OBE) implementation relates to foundational competence and learning outcomes among first-semester vocational students remains limited. Objective: This study examined the associations between OBE implementation, initial competence, and learning outcomes. Methods: A quantitative, cross-sectional survey of all 25 eligible first-semester students employed a 35-item, five-point Likert questionnaire. The proposed relationships were analyzed using partial least squares structural equation modeling (PLS-SEM). Results: OBE implementation was positively associated with initial competence ($\beta = 0.839$, $p < 0.001$), while its direct association with learning outcomes was not significant ($\beta = 0.101$, $p = 0.395$). Initial competence was positively associated with learning outcomes ($\beta = 0.850$, $p < 0.001$). The model explained 70.4% of the variance in initial competence and 87.7% in learning outcomes. Implications: Structured learning objectives and early academic support may benefit first-semester students. Novelty: The model considers foundational competence as a potential linking construct in early vocational education. The indirect effect requires separate bootstrap verification; the cross-sectional design does not establish causal improvement.

Keywords: Initial competence; Learning outcomes; Outcome-based education; Structural equation modeling; Vocational education

Introduction

Higher education increasingly requires graduates to demonstrate measurable competencies aligned with professional demands (Pramesti et al., 2024). Outcome-Based Education (OBE) addresses this expectation by aligning teaching activities and assessment with intended learning outcomes. For new vocational students, however, the transition to higher education also involves adapting to independent learning and discipline-specific concepts (Fajrianti et al., 2023).

The principles of outcome-based education emphasize explicitly defined demonstrations of learning, while constructive alignment connects intended outcomes, learning activities, and assessment (Biggs, 1996; Spady, 1994).

OBE implementation can be examined through the clarity of learning objectives, the alignment of instructional materials and assignments, and the lecturer's facilitative role (Wijaya et al., 2025). These components may be particularly relevant in introductory courses, where students establish learning routines and foundational conceptual understanding. Evidence from OBE-oriented instructional practice supports the relevance of outcome alignment for student understanding and performance (Sari et al., 2024).

Aligned assessment and purposeful feedback can support students' longer-term learning and self-regulation (Boud et al., 2006; Nicol et al., 2006). Feedback literacy further explains why students must interpret feedback and act on it, rather than merely receive

How to Cite:
Lubis, A. L., & Silitonga, F. (2026). The Effectiveness of OBE Learning Implementation in Improving Initial Competencies and Learning Outcomes of New Students. *Jurnal Penelitian Pendidikan IPA*, *12*(11), 110–120. https://doi.org/10.29303/jppipa.v12i11.13829

assessment information (Carless et al., 2018; Hattie et al., 2007).

An unresolved issue is the relationship between OBE implementation and students' initial competence. Initial competence conventionally refers to baseline knowledge and readiness at entry (Wulandari et al., 2024; Yuliana, 2021). In this study, however, the construct was reported by students at the end of the semester; it therefore represents retrospective, self-reported foundational competence rather than an independently administered entry test. This distinction constrains interpretation of any apparent improvement. Prior achievement, study habits, and learning-related psychological factors have also been associated with university performance, reinforcing the need to distinguish entry characteristics from outcomes measured later (Credé et al., 2008; Richardson et al., 2012).

The adjustment to higher education is also shaped by students' integration into the academic environment, which makes transition-related readiness a relevant consideration (Tinto, 1993). Longitudinal evidence on first-year engagement also emphasizes interactions between institutional conditions and students' individual experiences (Kahu et al., 2020).

Existing studies have addressed the implementation and perceived benefits of OBE, but evidence on the joint relationships of OBE implementation, foundational competence, and learning outcomes during the first semester remains limited in the specific vocational context examined here (Asbari et al., 2024; Gea et al., 2024). Further, the relationship between two questionnaire-based competence constructs may partly reflect shared measurement conditions. A structural model can explore these associations, but it cannot by itself identify changes over time or establish causality. Research on learning patterns and self-regulated learning provides further grounds for considering students' approaches to learning while avoiding claims that one-time surveys capture developmental change (Panadero, 2017; Vermunt et al., 2017).

Accordingly, this study examines three relationships among first-semester vocational students: (1) OBE implementation and foundational competence, (2) OBE implementation and perceived learning outcomes, and (3) foundational competence and perceived learning outcomes. Its contribution is a context-specific analysis that places foundational competence within the same model as OBE implementation and learning outcomes, rather than examining only a single direct relationship.

The conceptual model (Figure 1) specifies three positive associations: H1, OBE implementation with foundational competence; H2, OBE implementation with learning outcomes; and H3, foundational competence with learning outcomes. An indirect pathway is conceptually plausible, but its statistical significance must be determined from bootstrapped specific indirect effects rather than inferred from the direct paths alone.

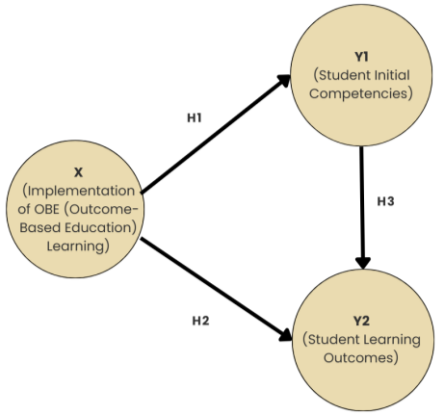


Figure 1. Research framework

Method

Research Design and Setting. This quantitative cross-sectional study examined first-semester vocational students enrolled in Introduction to Business Devices and English courses at Batam Tourism Polytechnic, Batam, Indonesia. The eligible population consisted of 25 students, and total sampling was used. All 25 students were included. The study describes associations between survey constructs; it does not compare pre- and post-intervention measurements. The exact survey administration dates should be inserted from the research records before resubmission.

Instruments and Measurement. A 35-item questionnaire using a five-point Likert response format assessed OBE implementation (X; 16 items: clarity of objectives, alignment of materials, assignments, and lecturer facilitation), self-reported foundational competence (Y1; 8 items: basic conceptual understanding, learning readiness, and organization of information), and perceived learning outcomes (Y2; 11 items: application of concepts, learning autonomy, and self-reported achievement). The items underwent content review by two experts. Since Y1 and Y2 were measured by self-report at the end of the semester, neither is an objective baseline test or independent academic-grade record.

Research Procedure and Data Analysis. Following course delivery, an online questionnaire was administered to the 25 eligible students. Responses were analyzed using SmartPLS and partial least squares structural equation modeling (PLS-SEM). Reflective measurement quality was examined using outer

loadings, composite reliability, Cronbach's alpha, average variance extracted, and cross-loadings; discriminant validity also requires verification using HTMT. The structural model was assessed through path coefficients, bootstrapped t statistics and p values, R^2, and f^2. Bootstrapped specific indirect effects and confidence intervals should be reported before a mediation claim is made. The SmartPLS project and original respondent-level data should be checked to confirm that all reported statistics use n = 25.

For transparent PLS-SEM reporting, measurement quality, structural estimates, and predictive assessment should be distinguished (Hair et al., 2019; Sarstedt et al., 2025; Shmueli et al., 2019). Comprehensive PLS-SEM guidance also recommends transparent justification of model specification, sample adequacy, mediation tests, and interpretive limitations (Hair et al., 2017).

Methodological Considerations. Total sampling covers the defined class but does not eliminate small-sample uncertainty or support population-wide generalization. A formal power assessment was not supplied. As the same respondents completed all constructs in one questionnaire, common-method variance and overlap between perceived foundational competence and perceived learning outcomes are possible. No longitudinal or control-group design was implemented; consequently, results are interpreted as associations, not causal effects or demonstrated gains.

Because all three constructs were assessed in the same questionnaire, common-method bias is a further potential limitation (Podsakoff et al., 2003).

Result and Discussion

Survey responses were collected from 25 first-semester students enrolled in Introduction to Business Devices and English courses. The sample size is corrected from 40 to 25 to match the actual population and total-sampling procedure. The following numerical output is retained from the supplied manuscript pending confirmation that the original SmartPLS analysis was run exclusively on these 25 cases; the coefficients should not be presented as newly recalculated estimates.

Measurement Model: Indicator Reliability and Validity

The results of the measurement model evaluation indicate that most indicators across the three research constructs have outer loading values above 0.70, demonstrating that these indicators adequately and strongly represent their respective latent constructs. For the OBE Implementation construct (X), nearly all indicators fall within the loading range of 0.764 to 0.880, categorized as "Very Strong." This suggests that aspects such as the clarity of learning objectives, relevance of course materials, effectiveness of assignments, and the lecturer's role as a facilitator were consistently perceived by students and accurately reflect the OBE construct. Only one indicator, X16, has a loading value of 0.588, which is below the ideal threshold of 0.70. This indicator is categorized as "Needs Evaluation," meaning it should be considered for further assessment to determine whether it should be retained, revised, or removed if it compromises convergent validity in subsequent stages. Nonetheless, because its value remains above the minimum acceptable threshold of 0.50 in exploratory PLS-SEM contexts, the indicator may still be retained provided there is strong theoretical justification.

Table 1. Outer Loadings

Indicator	Latent Variables	Outer Loading	Interpretation
X1	X	0.804	Very Strong
X2	X	0.799	Very Strong
X3	X	0.816	Very Strong
X4	X	0.854	Very Strong
X5	X	0.872	Very Strong
X6	X	0.839	Very Strong
X7	X	0.764	Very Strong
X8	X	0.811	Very Strong
X9	X	0.731	Valid
X10	X	0.835	Very Strong
X11	X	0.824	Very Strong
X12	X	0.764	Very Strong
X13	X	0.782	Very Strong
X14	X	0.880	Very Strong
X15	X	0.849	Very Strong
X16	X	0.588	Need Evaluation
Y1.1	Y	0.702	Valid
Y1.2	Y	0.905	Very Strong
Y1.3	Y	0.873	Very Strong
Y1.4	Y	0.797	Very Strong
Y1.5	Y	0.716	Valid
Y1.6	Y	0.873	Very Strong
Y1.7	Y	0.871	Very Strong
Y1.8	Y	0.833	Very Strong
Y2.1	Y	0.841	Very Strong
Y2.2	Y	0.689	Valid
Y2.3	Y	0.810	Very Strong
Y2.4	Y	0.888	Very Strong
Y2.5	Y	0.874	Very Strong
Y2.6	Y	0.882	Very Strong
Y2.7	Y	0.779	Very Strong
Y2.8	Y	0.885	Very Strong
Y2.9	Y	0.841	Very Strong
Y2.10	Y	0.689	Valid
Y2.11	Y	0.810	Very Strong

For the Initial Student Competence construct (Y1), the outer loading results also demonstrate a very strong

pattern. Most indicators show high loading values—such as 0.905, 0.873, 0.871, and 0.833—indicating that these items contribute substantially to the formation of the latent variable. Indicators Y1.1 and Y1.5, with loading values of 0.702 and 0.716 respectively, also meet the validity criteria, as they exceed the minimum threshold of 0.70. Overall, the Initial Student Competence construct can be concluded to have strong and consistent measurement quality in capturing students' perceptions related to foundational understanding, academic readiness, and their ability to organize information.

The Student Learning Outcomes construct (Y2) demonstrates excellent performance, with most indicators showing high loading values ranging from 0.779 to 0.888, all of which fall into the "Very Strong" category. This indicates that indicators such as advanced conceptual understanding, the ability to apply theory in assignments, improved learning independence, and overall academic achievement are consistently reflected by the respondents. Only two indicators—Y2.2 and Y2.10—have loading values of 0.689, which are slightly below the ideal threshold of 0.70 but still considered "Valid." These values remain acceptable because they fall within the tolerance range and do not diminish the overall reliability of the model. Additionally, the supplementary indicator Y2.11 shows a loading value of 0.810, indicating a very strong contribution to the construct.

Cross-loading results in Table 2 require verification against the original SmartPLS export. As printed, X9 loads more strongly on Y2 (0.770) than on X (0.731), and X16 loads more strongly on Y1 (0.675) than on X (0.588). Moreover, some reported Y2 rows appear duplicated from X rows and do not match the outer loadings in Table 1. Therefore, discriminant validity cannot be confirmed from the current table. Corrected cross-loadings and HTMT statistics are needed before making such a claim.

Although several Y1 indicators have higher loadings on Y1 than on the other constructs, high correlations between Y1 and Y2 suggest a potential lack of construct distinctiveness. An HTMT assessment should be reported with the verified measurement-model output.

The printed Y2 cross-loading entries do not consistently correspond to the reported Y2 outer loadings. They are retained only as the supplied, unverified figures, and their substantive interpretation is suspended until a corrected export is available.

Table 2. Indicator Cross-Loadings

Indicator	X1	Y1	Y2
X1	0.804	0.638	0.625
X2	0.799	0.675	0.676
X3	0.816	0.581	0.597
X4	0.854	0.620	0.584
X5	0.872	0.711	0.663
X6	0.839	0.728	0.637
X7	0.764	0.598	0.577
X8	0.811	0.579	0.563
X9	0.731	0.728	0.770
X10	0.835	0.697	0.650
X11	0.824	0.677	0.665
X12	0.764	0.614	0.549
X13	0.782	0.600	0.600
X14	0.880	0.754	0.729
X15	0.849	0.794	0.809
X16	0.588	0.675	0.646
Y1.1	0.676	0.702	0.642
Y1.2	0.775	0.905	0.826
Y1.3	0.785	0.873	0.804
Y1.4	0.705	0.797	0.787
Y1.5	0.713	0.716	0.659
Y1.6	0.635	0.873	0.823
Y1.7	0.584	0.871	0.840
Y1.8	0.644	0.833	0.757
Y2.1	0.804	0.638	0.625
Y2.2	0.799	0.675	0.676
Y2.3	0.816	0.581	0.597
Y2.4	0.854	0.620	0.584
Y2.5	0.872	0.711	0.663
Y2.6	0.839	0.728	0.637
Y2.7	0.764	0.598	0.577
Y2.8	0.811	0.579	0.563
Y2.9	0.731	0.728	0.770
Y2.10	0.835	0.697	0.650
Y2.11	0.824	0.677	0.665

Table 3. Construct Reliability and Convergent Validity

Variable	Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
X	0.963	0.965	0.967	0.646
Y1	0.931	0.934	0.944	0.680
Y2	0.957	0.960	0.963	0.701

The results of the construct reliability evaluation show that all latent variables in this study exhibit a very high level of internal consistency. The Cronbach's Alpha values for the three constructs—OBE Implementation (X), Initial Competence (Y1), and Learning Outcomes (Y2)—are 0.963, 0.931, and 0.957, respectively. All three values are well above the minimum threshold of 0.70, indicating that the items within each construct demonstrate strong homogeneity and consistently measure the same underlying concept. These high alpha

values reinforce the conclusion that the instrument used in this study possesses excellent internal reliability.

Table 4. Indicator Variance Inflation Factors

Indicator	VIF	Description
X1	3.875	Moderate Multicollinearity
X2	6.176	High Multicollinearity
X3	7.990	High Multicollinearity
X4	16.180	High Multicollinearity
X5	13.917	High Multicollinearity
X6	13.751	High Multicollinearity
X7	6.554	High Multicollinearity
X8	10.261	High Multicollinearity
X9	5.268	High Multicollinearity
X10	9.091	High Multicollinearity
X11	8.536	High Multicollinearity
X12	3.634	Moderate Multicollinearity
X13	6.224	High Multicollinearity
X14	11.780	High Multicollinearity
X15	6.732	High Multicollinearity
X16	2.248	Moderate Multicollinearity
Y1.1	1.913	Moderate Multicollinearity
Y1.2	5.065	High Multicollinearity
Y1.3	6.005	High Multicollinearity
Y1.4	3.282	Moderate Multicollinearity
Y1.5	2.175	Moderate Multicollinearity
Y1.6	7.495	High Multicollinearity
Y1.7	6.156	High Multicollinearity
Y1.8	3.485	Moderate Multicollinearity
Y2.1	3.875	Moderate Multicollinearity
Y2.2	6.176	High Multicollinearity
Y2.3	7.990	High Multicollinearity
Y2.4	16.180	High Multicollinearity
Y2.5	13.917	High Multicollinearity
Y2.6	13.751	High Multicollinearity
Y2.7	6.554	High Multicollinearity
Y2.8	10.261	High Multicollinearity
Y2.9	5.268	High Multicollinearity
Y2.10	9.091	High Multicollinearity
Y2.11	8.536	High Multicollinearity

In addition, the Composite Reliability values—both rho_A and rho_C—also demonstrate excellent results. The OBE Implementation construct (X) has a rho_A value of 0.965 and a rho_C value of 0.967; the Initial Competence construct (Y1) has a rho_A value of 0.934 and a rho_C value of 0.944; and the Learning Outcomes construct (Y2) has a rho_A value of 0.960 and a rho_C value of 0.963. All of these values exceed the minimum standard of 0.70 and even surpass the ideal threshold of 0.90 commonly recommended for confirmatory research. This indicates that the measurement model possesses a very high level of reliability, and that the indicators consistently represent their respective latent variables. The high composite reliability values suggest that the instrument is not only internally reliable but also stable in measuring the constructs when applied in different contexts. Discriminant validity should not be inferred from satisfactory reliability alone; the heterotrait–monotrait ratio (HTMT) provides an additional diagnostic (Henseler et al., 2015).

Convergent validity was evaluated using the Average Variance Extracted (AVE) values. Construct X obtained an AVE of 0.646, Y1 an AVE of 0.680, and Y2 an AVE of 0.701. All AVE values exceed the minimum threshold of 0.50, indicating that more than 50% of the variance in each construct's indicators is explained by its respective latent variable. In other words, the indicators demonstrate strong capability in reflecting their intended constructs. AVE values ranging from 0.64 to 0.70 signify a very good level of convergent validity and confirm that the model is adequate for proceeding to the structural model evaluation stage.

Indicator variance inflation factors are reported in Table 4. Several values exceed 10, indicating substantial collinearity among indicators. In a reflective measurement specification, high indicator VIF alone does not establish structural predictor collinearity, and high reliability does not resolve conceptual redundancy. The item set and measurement specification should therefore be revisited; structural predictor VIF values should be checked separately.

Structural Model: Effect Sizes and Explained Variance

The evaluation of effect size (f^2) was conducted to determine the contribution of each exogenous variable to the endogenous variable in the structural model. The f^2 value reflects the extent to which the R-square of a construct change when a specific predictor is removed from the model, thereby indicating the strength of each relationship. Referring to Cohen's (1988) criteria, an f^2 value of 0.02 is considered small, 0.15 is moderate, 0.35 is large, and values exceeding 1.00 indicate a very strong or substantial effect.

Table 5. Effect-Size Matrix (f^2)

Variable	X	Y1	Y2
X		2.379	0.025
Y1			1.731
Y2			

The results of the analysis show that the OBE Implementation construct (X) has a very large effect size on Students' Initial Competence (Y1), with an f^2 value of 2.379. This value far exceeds the threshold for a large effect (0.35), indicating that the implementation of OBE-based learning makes a very strong contribution to shaping the initial competence of first-semester students. This finding validates the assumption that an outcome-based learning approach, when implemented systematically, plays a crucial role in building the foundational understanding and academic readiness of new students (Sari et al., 2024).

In addition, the Initial Competence construct (Y1) also shows a very large effect size on Learning Outcomes (Y2), with an f^2 value of 1.731. This value indicates that initial competence is not only influential but is one of the most dominant factors in determining students' learning achievement. In other words, the stronger the students' initial ability to understand basic concepts and organize information, the higher their academic performance will be at the end of the course.

Meanwhile, the f^2 value for the effect of variable X on Y2, which is 0.025, indicates a small effect size. This finding means that the direct contribution of OBE implementation to learning outcomes is relatively small when not accompanied by an improvement in students' initial competence. Although the direct effect is minimal, this result suggests the presence of a potential indirect (mediated) relationship, in which most of the influence of OBE implementation on learning outcomes is channeled through the enhancement of students' initial competence. This pattern supports the theoretical framework that initial competence is an important mechanism explaining how outcome-based learning strategies affect academic performance.

Table 6. Coefficient of Determination (R^2)

Variable	R-Square	R-Square Adjusted
Y1	0.704	0.697
Y2	0.877	0.870

The R-square value is used to evaluate the extent to which the independent variables in the model are able to explain the dependent variable. In the context of PLS-SEM, an R-square value of 0.25 is considered weak, 0.50 moderate, and 0.75 or higher is considered strong. Based on the analysis results, the construct of Students' Initial Competence (Y1) has an R-square value of 0.704. This means that 70.4% of the variability in students' initial competence can be explained by the implementation of OBE-based learning (X). This value falls into the strong category, indicating that the outcome-based learning approach (OBE) has a substantial contribution to shaping the foundational abilities of first-semester students.

Meanwhile, the construct of Student Learning Outcomes (Y2) shows an R-square value of 0.877. This finding indicates that 87.7% of the variation in student learning outcomes can be explained by the combined influence of OBE Implementation (X) and Students' Initial Competence (Y1). This value far exceeds the threshold for the "strong" category and provides evidence that the research model possesses very high predictive power. In other words, students' success in achieving learning outcomes at the end of the course is strongly influenced by the quality of OBE implementation as well as the strength of their initial competence.

The relatively high R^2 values describe in-sample explained variance; they do not demonstrate absence of overfitting or establish out-of-sample predictive validity. An evaluation of predictive performance would require additional evidence such as PLS predict or appropriate out-of-sample validation.

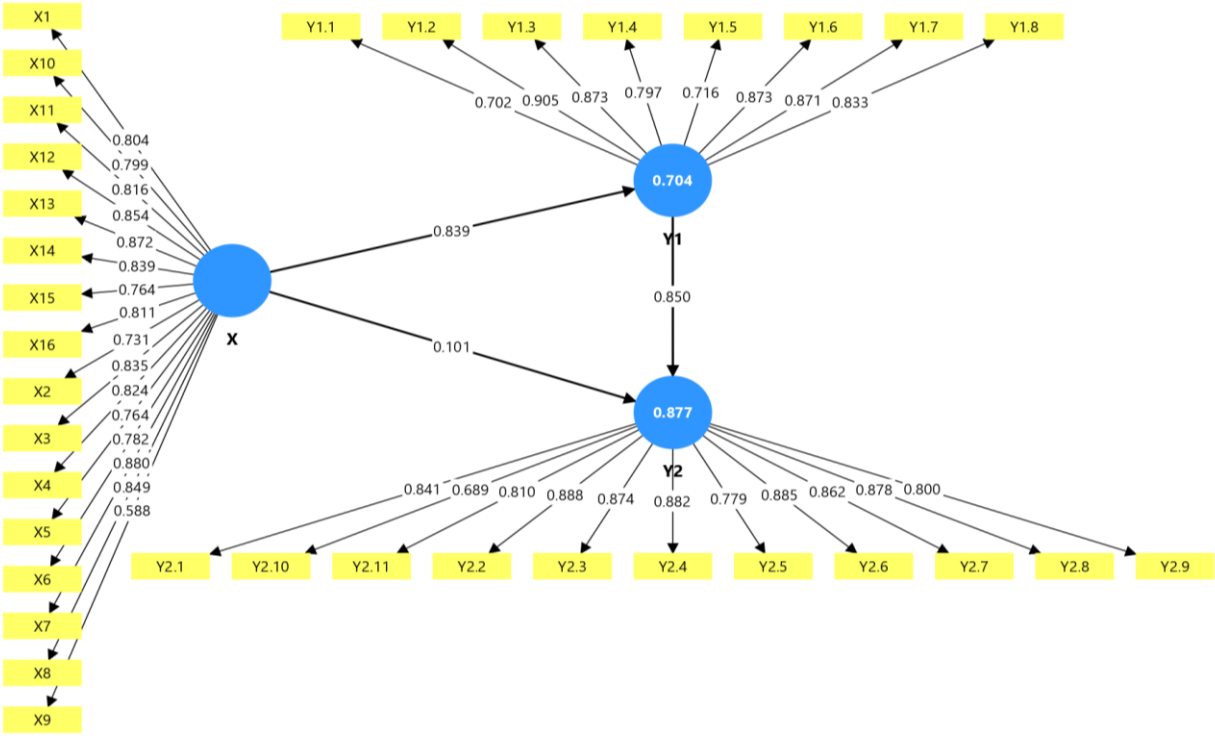


Figure 2. Graphic output of research model

The path model diagram from the PLS-SEM analysis provides a visual representation of the relationships among the latent constructs in this study, while also showing the indicators that form each construct. The OBE Implementation construct (X) appears as an exogenous variable with two direct paths, namely toward Students' Initial Competence (Y1) and Students' Learning Outcomes (Y2). The path coefficient from X to Y1 is 0.839, indicating that the implementation of OBE-based learning exerts a very strong influence on the formation of students' initial competence. This magnitude is consistent with the previously reported f-square value, which shows that OBE is the dominant predictor in explaining the Y1 construct.

Meanwhile, the path from X to Y2 has a coefficient of 0.101, indicating a relatively small direct effect on students' learning outcomes. This magnitude is consistent with the very small f-square value for the X → Y2 relationship, providing an early indication that the implementation of OBE does not directly improve learning outcomes except through another mechanism—namely, by enhancing students' initial competence. This pattern supports the likelihood of a strong mediating effect within the structural model.

The construct of Initial Competence (Y1) then shows a very strong influence on Learning Outcomes (Y2), with a path coefficient of 0.850. This value reinforces earlier findings indicating that initial competence is the strongest predictor of students' learning outcomes. Both visually and numerically, this relationship represents the primary pathway explaining the contribution of variables in the model. When combined with the R-square value of 0.877 for Y2, it can be concluded that the majority of students' learning achievement is explained by the strength of their initial competence.

The indicators of each construct are also presented in the diagram with high outer loading values, showing that all indicators make a significant contribution to measuring their respective latent constructs. The loading values range from 0.588 to 0.905, with most indicators scoring above 0.75, indicating strong and consistent representational power for each construct. This supports the conclusion that the measurement model is valid and reliable prior to conducting the structural model analysis.

Hypothesis Testing and Interpretation

The path coefficients table presents the results of testing the relationships among latent variables in the structural model using the bootstrapping procedure. The evaluation is based on the values of the original sample (O), t-statistics, and p-values, which determine whether the relationships between constructs are statistically significant. In this study, a significance level of $p < 0.05$ was used.

Table 7. Structural Path Coefficients

Correlation	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
X → Y1	0.839	0.834	0.065	12.863	0.000
X → Y2	0.101	0.100	0.119	0.850	0.395
Y1 → Y2	0.850	0.847	0.107	7.949	0.000

OBE Implementation and Foundational Competence

The results indicate that the path coefficient from X to Y1 is 0.839, with a t-statistic of 12.863 and a p-value of 0.000. This value far exceeds the threshold of $t > 1.96$ for a 5% significance level. Thus, hypothesis H1 is accepted, meaning that the implementation of OBE-based learning has a positive and significant effect on students' initial competencies. This finding is consistent with the very large f-square value (2.379) and the high R-square of Y1 (0.704), confirming that OBE serves as the primary predictor of students' initial academic competence.

OBE Implementation and Learning Outcomes

The path coefficient for X → Y2 is 0.101, with a t-statistic of 0.850 and a p-value of 0.395. The p-value, which is far above 0.05, indicates that this relationship is not statistically significant. Therefore, hypothesis H2 is rejected, as the implementation of OBE does not show a significant direct effect on students' learning outcomes. This result aligns with the earlier finding from the f-square value (0.025), which indicates a very small effect size. Accordingly, it can be concluded that the contribution of OBE to learning outcomes operates primarily through an indirect mechanism, namely via students' initial competencies as a mediating variable.

Foundational Competence and Learning Outcomes

The path coefficient for Y1 → Y2 is 0.850, with a t-statistic of 7.949 and a p-value of 0.000, indicating a highly significant statistical relationship. Thus, hypothesis H3 is accepted, demonstrating that students' initial competencies have a positive and significant effect on their learning outcomes. This finding is consistent with the very large f-square value (1.731) and the high R-square for Y2 (0.877), confirming that initial competency is the strongest predictor of first-semester students' learning achievement.

The correlation table among latent variables illustrates the linear relationships between the constructs of OBE Implementation (X), Initial Competence (Y1), and Learning Outcomes (Y2). These correlations provide a preliminary overview of the direction and strength of the relationships before further examination through the structural model. Generally, higher correlation values indicate stronger relationships between constructs, with values ranging from –1 to +1. The results show that the correlation between OBE Implementation (X) and Initial Competence (Y1) is 0.839, which falls into the category of a very strong and positive relationship. This reinforces earlier findings from the path coefficients and f-square analysis, indicating that the implementation of OBE-based learning is closely associated with the enhancement of students' initial competencies (Asbari et al., 2024). This high correlation highlights the consistency between the empirical relationship patterns and the theoretical foundation of outcomes-based education, wherein structured and goal-oriented learning strategies help build a strong academic foundation for first-year students.

Table 8. Latent Variable Correlations

	X	Y1	Y2
X	1.000	0.839	0.814
Y1	0.839	1.000	0.935
Y2	0.814	0.935	1.000

Furthermore, the correlation between Initial Competence (Y1) and Learning Outcomes (Y2) is 0.935, which is the highest correlation value in the model. This exceptionally strong correlation indicates that students with higher levels of initial competence tend to achieve better learning outcomes. This result is consistent with the path coefficient of Y1 → Y2, which is 0.850 and statistically significant in the bootstrapping test, as well as the high R-square value for Y2 (0.877). Thus, this correlation strengthens the empirical evidence that initial competence is a key variable in determining students' academic success.

The OBE–learning outcomes latent-variable correlation was 0.814, whereas the adjusted direct path was not statistically significant (β = 0.101, p = 0.395). A strong bivariate correlation combined with a nonsignificant adjusted path is compatible with shared variance among predictors; it does not prove full mediation. Formal bootstrapping of the specific indirect effect is required.

The findings indicate that the implementation of Outcome-Based Education (OBE) has a very strong influence on the development of students' initial competencies, as evidenced by a high path coefficient (0.839), significant t-statistic, and a substantial f-square value (2.379). These results consistently support OBE theory, which emphasizes that learning processes must be systematically designed to ensure all students achieve fundamental learning outcomes (Nadilah et al., 2025). In the context of vocational education, these findings align with research by Halim (2025) which demonstrates that outcome-based instructional design can enhance students' readiness, particularly in preparing for the workforce. Thus, this study strengthens the argument that OBE serves as an effective pedagogical framework for fostering initial competencies, especially among first-semester students who are still navigating their academic transition.

The influence of initial competencies on students' learning outcomes was also found to be highly significant, as reflected in a path coefficient of 0.850 and an f-square value of 1.731. This strong relationship demonstrates that initial competence is a key determinant of students' academic achievement. This finding aligns with the learning progression model (Muninggar et al., 2023), which explains that successful learning is largely determined by the foundational abilities possessed by learners. Previous studies, such as those by Zahroh et al. (2024) and local research in vocational higher education (Ansori et al., 2025), likewise emphasize that basic competencies are the primary determinants of success in courses requiring technical and systematic conceptual understanding. Thus, the present study not only confirms established theoretical perspectives but also strengthens empirical evidence within the context of vocational education in Indonesia.

The difference between the OBE–learning outcomes correlation (0.814) and direct path (0.101, p = 0.395) illustrates why the adjusted structural results should not be conflated with simple associations. Given the strong Y1–Y2 correlation (0.935), the distinctiveness of the constructs also merits examination with verified cross-loadings and HTMT values.

Structurally, the research model demonstrates exceptionally strong explanatory power, as indicated by an R-square value of 0.704 for Initial Competence and 0.877 for Learning Outcomes. These high R-square values suggest that the model successfully captures the most relevant variables in explaining the variation in students' learning outcomes, consistent with the recommendations of Mardiana et al. (2019) for high-quality PLS-SEM models. This finding also provides a significant contribution to the OBE literature in Indonesia, which has largely focused on perceptions or evaluative implementation studies rather than structural modeling of interrelationships among learning components, as undertaken in this research. Thus, the study offers a new perspective on how OBE functions

mechanistically within the context of early-stage vocational student learning.

Furthermore, the strong relationship observed between Y1 → Y2 reinforces previous literature emphasizing the critical role of foundational competencies as predictors of academic performance. The study by Sya'roni (2018) in the context of technology and business education demonstrated that students with low initial competence tend to fail in achieving learning outcomes, even when effective instructional models are implemented. The present study reveals a similar pattern: OBE functions effectively only when students' initial competencies are well established. Therefore, these findings carry important implications for vocational education institutions, suggesting the need to focus not only on the design of OBE-based instruction but also on strengthening students' foundational competencies from the beginning of the semester. This can be achieved through initiatives such as bridging courses, digital literacy training, and reinforcement of fundamental conceptual understanding. These interpretations are consistent with broader evidence that academic achievement reflects multiple student characteristics and study-related factors rather than a single instructional input (Richardson et al., 2012).

Taken together, the reported coefficients suggest that perceived OBE implementation is associated with students' self-reported foundational competence and that competence is associated with perceived learning outcomes. However, the specific indirect effect was not supplied, so claims of full mediation are premature. Relative to studies primarily describing OBE adoption or course-level perceptions (Asbari et al., 2024), this study examines these three relationships together within one first-semester vocational class. This is a contextual contribution rather than proof of causal effectiveness.

Conclusion

Among 25 first-semester vocational students, the reported structural model indicates a positive association between perceived OBE implementation and foundational competence ($\beta = 0.839$, $p < 0.001$), as well as between foundational competence and perceived learning outcomes ($\beta = 0.850$, $p < 0.001$). The direct OBE–learning outcomes path was not significant ($\beta = 0.101$, $p = 0.395$). The model reported R^2 values of 0.704 and 0.877 for competence and learning outcomes, respectively. These figures remain subject to verification against SmartPLS output for n = 25. The sample is small and drawn from one instructional setting; data are cross-sectional and self-reported, and discriminant validity and the indirect effect require further verification. For practice, lecturers may explicitly communicate course outcomes, introduce diagnostic checks in the first weeks, and provide targeted support in foundational concepts; subsequent evaluations should use baseline and final performance assessments to test actual improvement. The study's contribution is the joint examination of three constructs in early vocational learning, not a causal demonstration of OBE effectiveness.

Acknowledgments
The authors sincerely thank all parties whose support contributed to the completion of this research, including the academic leadership, colleagues, and students who participated and provided valuable input.

Author Contributions
Arina Luthfini Lubis (first and corresponding author) led the conceptualization, research design, instrument development, data collection, formal analysis, interpretation of findings, manuscript drafting, revision, and finalization. Frangky Silitonga contributed to data validation and verification of the analytical results. Both authors reviewed and approved the final manuscript.

Funding
This research received no external funding or financial support.

Conflicts of Interest
The authors declare no conflicts of interest.

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