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Structural Equation Modeling and Machine Learning Analysis of Factors Influencing Students' Entrepreneurial Intention

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ABSTRACT
Entrepreneurial intention has become a critical issue in higher education, yet previous studies have primarily relied on explanatory models without integrating predictive approaches to identify the most influential determinants. This study aims to examine the relationships among organizational experience, campus support, entrepreneurial training, risk perception, social capital, and entrepreneurial intention by integrating Structural Equation Modeling (SEM) and Machine Learning (ML). Data were analyzed using covariance-based SEM to examine structural relationships and ML techniques to validate predictive performance and identify the most important predictors. The findings reveal that social capital is the only variable with a significant positive effect on entrepreneurial intention, whereas organizational experience, campus support, entrepreneurial training, and risk perception do not show significant direct effects. ML analysis consistently confirms social capital as the strongest predictor of entrepreneurial intention, supporting the robustness of the SEM findings while providing complementary predictive insights. The integration of SEM and ML represents the main contribution of this study by combining explanatory and predictive perspectives to obtain a more comprehensive understanding of entrepreneurial intention. These findings suggest that universities should prioritize strengthening students' social capital through collaborative networks, mentoring, and community engagement to foster entrepreneurial intention more effectively.

Keywords: *Entrepreneurial Intention, Social Capital, Structural Equation Modeling, Machine Learning, Higher Education*

1. Introduction

Entrepreneurial intention has long been recognized as a crucial antecedent of entrepreneurial behavior and a key indicator of future entrepreneurial activity, particularly among university students (Montero-Benavides et al., 2026). In the context of higher education, students represent a strategic group for entrepreneurship development, as they are expected to become agents of innovation, job creators, and contributors to economic resilience. Universities worldwide have increasingly integrated entrepreneurship education, organizational experiences, and institutional support systems to foster students' entrepreneurial intention (Xanthopoulou & Sahinidis, 2024). However, despite extensive efforts, empirical findings on the determinants of students' entrepreneurial intention remain inconsistent and context-dependent, indicating the need for more comprehensive and methodologically robust investigations.

Previous studies have identified various psychological, social, and institutional factors influencing entrepreneurial intention, including organizational experience, campus support, entrepreneurial training, risk perception, and social capital (Aka & Enagogo, 2025; Ngoc Luu & Hue, 2026). Although these variables have been widely examined, empirical findings remain inconsistent across different educational and cultural contexts. Organizational experience has been reported to positively influence entrepreneurial intention in some studies by enhancing leadership skills, opportunity recognition, and entrepreneurial competence (Donaldson et al.,

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2025), whereas other studies found its effect to be weak or statistically insignificant. Likewise, campus support and entrepreneurial training have produced mixed results depending on institutional settings and program implementation, while evidence regarding risk perception remains inconclusive. In contrast, social capital has consistently emerged as an important determinant, although the magnitude of its influence varies considerably across studies. These inconsistencies indicate that the determinants of entrepreneurial intention remain far from conclusive and require further investigation using more comprehensive analytical approaches.

Although entrepreneurial intention has frequently been explained using well-established determinants such as entrepreneurial self-efficacy, attitude toward entrepreneurship, and perceived behavioral control, these variables have been extensively validated in previous research. This study instead focuses on organizational experience, campus support, entrepreneurial training, risk perception, and social capital because these factors represent contextual and institutional dimensions that universities can directly influence through entrepreneurship education, organizational activities, and campus policies. Consequently, examining these variables offers more practical implications for higher education institutions seeking to strengthen students' entrepreneurial intention.

Despite the growing body of literature, most existing studies examine these factors in isolation or through linear causal models, often assuming homogeneous effects across individuals (Senthil Kumar et al., 2026). Structural Equation Modeling (SEM) has been widely employed to test theoretical relationships among latent constructs and to validate causal pathways proposed by entrepreneurial intention theories, such as the Theory of Planned Behavior and Human Capital Theory(Duong, 2025). SEM provides a powerful framework for confirming measurement validity and estimating direct and indirect effects among variables(Hardin et al., 2026; Sharma et al., 2026; Zatini & Della Porta, 2025). However, SEM relies heavily on theoretical assumptions and linear relationships, which may limit its ability to capture complex, non-linear patterns inherent in human decision-making processes.

In parallel, recent advancements in data analytics have introduced Machine Learning (ML) as a promising approach in educational and entrepreneurial research (Celbiş, 2021; Stylianou & Pantelidou, 2025). Machine learning techniques excel in prediction-oriented tasks, feature selection, and uncovering hidden patterns within large and complex datasets (Laul & Galatro, 2025; Sabahi & Parast, 2020). Unlike traditional statistical models, ML does not require strict assumptions regarding data distribution or linearity, making it particularly suitable for modeling behavioral phenomena influenced by multiple interacting factors (Malik et al., 2023; Zhang & Cutumisu, 2024). In the context of entrepreneurial intention, ML has been increasingly used to identify dominant predictors, rank variable importance, and improve predictive accuracy.

The state of the art in entrepreneurial intention research indicates a gradual shift toward methodological hybridity (Laul & Galatro, 2025; Sabahi & Parast, 2020). Recent studies have begun to acknowledge that moderate explanatory or predictive performance should not be interpreted as a limitation, but rather as a reflection of the inherent complexity of entrepreneurial behaviour (Marengo et al., 2025). Entrepreneurial intention is shaped by multifaceted psychological, social, and contextual processes that cannot be fully captured by a single methodological approach. While SEM excels in testing hypothesized relationships and validating theoretical constructs, it may overlook non-linear interactions and variable dominance patterns (Wu et al., 2023). Conversely, ML can identify the most influential predictors but often fails to explain why such relationships occur.

Rather than being viewed as competing methodologies, SEM and ML should be considered complementary approaches. SEM provides theory-driven explanations by testing causal relationships among latent constructs, whereas ML offers data-driven insights by identifying dominant predictors and improving predictive performance. Integrating these approaches enables researchers to obtain both explanatory and predictive evidence, thereby providing a more comprehensive understanding of entrepreneurial intention than either method alone.

Despite this recognition, empirical studies that explicitly integrate SEM and ML within a single research design remain limited, particularly in the context of higher education students in developing countries. Most existing research still treats SEM and ML as competing approaches rather than complementary ones. Moreover, few studies have systematically compared SEM-based causal significance with ML-based predictive importance using the same set of variables. This gap limits our understanding of whether statistically significant relationships in SEM also function as dominant predictors in real-world decision-making contexts.

This study addresses these gaps by integrating Structural Equation Modeling and Machine Learning to analyze factors influencing students' entrepreneurial intention. Specifically, this research examines the roles of organizational experience, campus support, entrepreneurial training, risk perception, and social capital using SEM to test causal relationships and ML to validate predictive relevance. By employing this hybrid approach, the study seeks to move beyond traditional confirmation-based analysis toward a more holistic understanding of entrepreneurial intention.

The novelty of this study lies in its methodological integration and analytical perspective. First, it bridges theory-driven and data-driven paradigms by positioning SEM as an explanatory tool and ML as a predictive validation mechanism, rather than treating them as standalone or competing methods. Second, the study introduces a comparative interpretation of results, where SEM path significance is contrasted with ML feature importance to identify convergent and divergent findings. This allows for a more nuanced interpretation of entrepreneurial intention determinants, distinguishing between statistically significant effects and practically dominant predictors. Third, the study contributes empirical evidence from the higher education context in a developing economy, enriching the global discourse on entrepreneurial intention with context-sensitive insights.

Despite these methodological developments, several important research gaps remain. First, previous studies have predominantly relied on either Structural Equation Modeling or Machine Learning independently, resulting in fragmented explanatory and predictive evidence. Second, little is known about whether variables that are statistically significant in SEM also emerge as the most influential predictors when evaluated using ML techniques. Third, empirical evidence integrating both approaches remain scarce, particularly in higher education settings within developing countries, where entrepreneurial ecosystems differ substantially from those in developed economies. Addressing these gaps requires an integrated analytical framework capable of combining causal explanation with predictive validation.

From a practical perspective, the findings are expected to provide evidence-based guidance for universities and policymakers in designing entrepreneurship programs. Understanding which factors are causally significant and which are predictively dominant can help institutions prioritize interventions, allocate resources more effectively, and design entrepreneurship education that aligns with students' actual decision-making patterns. Furthermore, the hybrid SEM–ML approach offers a replicable analytical framework that can be applied to other educational and behavioral research contexts. Based on the above background, state of the art, and identified research gaps, this study formulates the following research questions:

1. To what extent do organizational experience, campus support, entrepreneurial training, risk perception, and social capital influence students' entrepreneurial intention based on Structural Equation Modeling analysis?
2. Which factors emerge as the most dominant predictors of students' entrepreneurial intention based on Machine Learning analysis?
3. How do the results of SEM-based causal relationships compare with ML-based predictive importance in explaining students' entrepreneurial intention?

2. Literature Review

The influence of organizational experience on entrepreneurial intention

Organizational experience refers to individuals' involvement in student organizations, professional associations, or extracurricular activities that foster leadership, teamwork, and problem-solving skills. From the perspective of Social Learning Theory, experiential learning enables individuals to acquire entrepreneurial competencies through observation, interaction, and practice. Previous studies suggest that organizational experience enhances self-efficacy and opportunity recognition, which are critical antecedents of entrepreneurial intention (Deliana, 2023; Z. M. Ye & Kang, 2025). However, empirical evidence remains mixed, as some studies indicate that organizational experience alone may not directly translate into entrepreneurial intention without sufficient contextual support (Lianto et al., 2025). Based on this theoretical reasoning, the following hypothesis is proposed: H1: Organizational experience has a positive effect on entrepreneurial intention.

The influence of campus support on entrepreneurial intention

Campus support reflects institutional mechanisms such as entrepreneurial ecosystems, mentoring programs, business incubators, and entrepreneurship-related policies provided by universities. Drawing on Institutional Theory, a supportive campus environment reduces structural barriers and enhances the perceived feasibility of entrepreneurship (Anjum et al., 2021; L. Ye et al., 2025). Empirical studies demonstrate that university support plays a significant role in shaping students' entrepreneurial intention by strengthening entrepreneurial attitudes and perceived behavioral control (Ayad et al., 2022). Nevertheless, other studies report that institutional support may exert only an indirect influence when personal resources are limited (M. Liu et al., 2022). Therefore, the following hypothesis is formulated: H2: Campus support has a positive effect on entrepreneurial intention.

The influence of entrepreneurial training on entrepreneurial intention

Entrepreneurial training aims to develop entrepreneurial knowledge, skills, and competencies related to opportunity identification and venture creation. According to Human Capital Theory, training investments enhance individuals' productive capabilities and confidence, thereby increasing their intention to engage in entrepreneurship (Martínez-Gregorio et al., 2021). Prior research confirms that entrepreneurship education and training positively influence entrepreneurial intention (Montes et al., 2023). However, some studies argue that training outcomes depend on pedagogical design and learners' motivation (Wang et al., 2025). Based on this argument, the following hypothesis is proposed: H3: Entrepreneurial training has a positive effect on entrepreneurial intention.

The influence of risk perception on entrepreneurial intention

Risk perception reflects individuals' subjective evaluation of uncertainty and potential loss associated with entrepreneurial activities. Grounded in Prospect Theory**,** individuals who perceive entrepreneurial risk as high tend to avoid entrepreneurial behavior, whereas those who perceive risk as manageable are more likely to pursue entrepreneurial opportunities (Malathi & Venugopal, 2025; Ying & Yaakob, 2025). Empirical studies consistently report a negative relationship between risk perception and entrepreneurial intention (Caputo et al., 2025; Yang et al., 2025). Accordingly, the following hypothesis is proposed: H4: Risk perception has a negative effect on entrepreneurial intention.

The influence of social capital on entrepreneurial intention

Social capital encompasses social networks, trust, and norms that facilitate access to information, resources, and support. Based on Social Capital Theory, strong social ties enhance opportunity recognition and reduce uncertainty in entrepreneurial decision-making (Mensah et al., 2021). Empirical evidence strongly supports the positive role of social capital in fostering entrepreneurial intention (Guevara-Otero et al., 2026; Li et al., 2025; Toh et al., 2025). Therefore, the following hypothesis is formulated: H5: Social capital has a positive effect on entrepreneurial intention.

The mediating role of entrepreneurial training and risk perception

Entrepreneurial training and risk perception are theoretically positioned as mediating mechanisms linking organizational experience, campus support, and social capital to entrepreneurial intention (Civelek et al., 2025). Organizational experience and campus support may enhance training effectiveness, while social capital may lower perceived risk through shared knowledge and emotional support (Solodoha & Mosi, 2025; Tian & Yang, 2025). However, empirical findings on these mediation effects remain inconclusive. Based on this conceptual framework, the following hypotheses are proposed:

H6: Entrepreneurial training mediates the relationship between organizational experience and entrepreneurial intention.

H7: Entrepreneurial training mediates the relationship between campus support and entrepreneurial intention.

H8: Entrepreneurial training mediates the relationship between social capital and entrepreneurial intention.

H9: Risk perception mediates the relationship between organizational experience and entrepreneurial intention.

H10: Risk perception mediates the relationship between campus support and entrepreneurial intention.

H11: Risk perception mediates the relationship between social capital and entrepreneurial intention.

2. Methods

This study adopted a quantitative research design with an explanatory and confirmatory approach to examine the relationships among organizational experience (PO), campus support (DK), entrepreneurial training (PK), risk perception (PR), social capital (MS), and entrepreneurial intention (IB). The primary objective was to test theoretically derived hypotheses and to assess both explanatory and predictive relationships by integrating Structural Equation Modeling (SEM) and Machine Learning (ML). This hybrid methodological approach combines theory-driven causal explanation with data-driven predictive validation, providing a more comprehensive understanding of entrepreneurial intention.

The target population consisted of undergraduate students enrolled in Management Study Programs at eight higher education institutions in Riau Province, Indonesia, namely Universitas Islam Riau, Universitas Riau, Universitas Islam Negeri Sultan Syarif Kasim Riau, Universitas Islam Indragiri, Universitas Muhammadiyah Riau (UMRI), Universitas Lancang Kuning, STIE Tuah Negeri, and STIE Bengkalis. These institutions comprise both public and private universities and were selected because they have incorporated entrepreneurship education through entrepreneurship courses, student organizations, and university-based entrepreneurial development programs. The respondents were considered appropriate because they represent potential nascent entrepreneurs whose entrepreneurial intentions are still developing.

A purposive sampling technique was employed to ensure that respondents met the inclusion criteria, namely: (1) being actively enrolled in a Management Study Program and (2) having prior exposure to entrepreneurship-related learning activities, including entrepreneurship courses, organizational participation, or entrepreneurship development programs.

Prior to the main survey, the research instrument underwent content validation and pilot testing. An initial questionnaire consisting of 115 items was developed based on well-established and validated scales adapted from previous entrepreneurship and management studies. The pilot study involved 45 undergraduate students who were not included in the final sample. Item validity analysis resulted in the removal of 17 items that did not satisfy the required validity criteria, leaving 98 valid items for use in the main survey.

The main survey was conducted between April and May using a structured online questionnaire. A total of 550 questionnaires were distributed to eligible students across the eight participating universities. Of these, 490 completed questionnaires were returned and retained for analysis, yielding a response rate of 89.1%. The final sample consisted of 490 undergraduate students, including 388 males (79.2%) and 102 females (20.8%). The inclusion of respondents from both public and private universities representing diverse institutional environments enhanced the representativeness and generalizability of the findings within the higher education context of Riau Province. Furthermore, the final sample size exceeded the minimum recommendation for covariance-based SEM, ensuring adequate statistical power and stable parameter estimation for both SEM and Machine Learning analyses.

Data were collected using a structured questionnaire developed from well-established and validated scales reported in previous entrepreneurship and management studies. All constructs were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Organizational experience was operationalized through indicators reflecting involvement in organizational activities, leadership roles, teamwork, and decision-making experiences. Campus support was measured through perceptions of institutional encouragement, the availability of entrepreneurial resources, mentoring, and supportive policies. Entrepreneurial training was assessed using indicators representing the relevance, quality, and applicability of entrepreneurship education and training. Risk perception was measured through perceived uncertainty, fear of failure, and tolerance toward entrepreneurial risk. Social capital was operationalized through indicators representing social networks, trust, peer support, and access to information and resources. Entrepreneurial intention was measured using indicators reflecting respondents' willingness, plans, and commitment to establish a business in the future.

Before conducting the main analyses, prerequisite tests were performed to ensure data quality and the suitability of the dataset for covariance-based SEM. Univariate normality was assessed using Z-skewness and Z-kurtosis values, with all variables falling within the acceptable range of ±1.96. Multivariate normality was evaluated using relative multivariate kurtosis, indicating that the assumption of multivariate normality was satisfied. Multicollinearity was examined using the correlation matrix among latent constructs, confirming that all correlation coefficients were below the recommended threshold of ±0.90. Multivariate outliers were assessed using Mahalanobis Distance, with all observations remaining below the critical chi-square value, allowing all responses to be retained. Linearity between independent variables and entrepreneurial intention was evaluated through scatterplots and significance testing, confirming that the linearity assumption was satisfied.

Structural Equation Modeling was performed using a covariance-based SEM approach following the recommended two-step procedure. The first stage evaluated the measurement model using Confirmatory Factor Analysis (CFA) to establish construct validity and reliability. Convergent validity was confirmed as all standardized factor loadings exceeded the recommended threshold of 0.60. Composite Reliability (CR) values for all constructs exceeded 0.70, indicating satisfactory internal consistency, while Average Variance Extracted (AVE) values were above 0.50, confirming adequate convergent validity.

The second stage evaluated the structural model to test the hypothesized relationships among variables. Model fit was assessed using multiple goodness-of-fit indices, including Chi-square, RMSEA, SRMR, GFI, AGFI, CFI, NFI, and IFI. Structural path coefficients and their corresponding t-values were examined to determine the significance of direct effects among variables. The coefficient of determination (R^2) was used to evaluate the explanatory power of the model for endogenous constructs, particularly entrepreneurial intention.

Mediation analysis was subsequently conducted within the SEM framework to examine the mediating roles of entrepreneurial training and risk perception. Direct and indirect effects were estimated by examining the relationships between independent variables, mediators, and entrepreneurial intention. This analysis enabled the identification of whether the effects of organizational experience, campus support, and social capital on entrepreneurial intention were transmitted through the proposed mediators or occurred primarily through direct pathways.

To strengthen predictive validation, Machine Learning analysis was employed as a complementary analytical approach. Regularized linear regression combined with tree-based validation techniques was used to evaluate the relative importance of predictors and identify the most informative variables influencing entrepreneurial intention. Feature selection procedures were implemented to eliminate redundant or weak predictors that did not improve model performance. Predictive performance was evaluated using the coefficient of determination (R^2), while the modeling strategy emphasized model parsimony, predictive stability, and minimal risk of overfitting.

The integration of SEM and Machine Learning provided complementary analytical perspectives by combining explanatory and predictive approaches within a unified research framework. SEM was employed to examine theory-driven structural relationships among latent constructs, whereas Machine Learning assessed predictive importance and validated the robustness of the identified determinants. The consistency between SEM and Machine Learning findings strengthened the credibility, robustness, and practical relevance of the results. All analyses were conducted using standard statistical software widely applied in SEM and Machine Learning research. Overall, the adopted methodological framework ensured analytical rigor through validated measurement instruments, systematic data screening, comprehensive assumption testing, and the integration of complementary analytical techniques, thereby providing a comprehensive understanding of the determinants of entrepreneurial intention in higher education.

3. Results and Discussion

Prior to conducting structural analysis using Structural Equation Modeling (SEM) and subsequent machine learning analysis, a series of prerequisite tests were performed to ensure that the research data met the required statistical assumptions. These tests included assessments of univariate and multivariate normality, multicollinearity, multivariate outliers, and linearity among variables. Verifying these assumptions is a crucial step in quantitative analysis, as they directly affect the accuracy of parameter estimation, the validity of hypothesis testing, and the reliability of the research findings. The fulfillment of all prerequisite criteria indicates that the proposed research model is suitable for further analysis using covariance-based SEM and machine learning approaches, allowing the results to be interpreted in a valid and scientifically sound manner. The results can be seen on Table 1, 2, 3, 4, 5, and 6.

Table 1. Normality Univariate Test

Variable	Z-Skewness	Z-Kurtosis	Conclusion
PO	1,24	1,31	Normal
DK	1,11	1,45	Normal
PK	0,97	1,22	Normal

PR	1,36	1,48	Normal
MS	1,08	1,19	Normal
IB	1,14	1,27	Normal

Based on the results of the normality test using Z-Skewness and Z-Kurtosis values, all research variables—PO, DK, PK, PR, MS, and IB—exhibited normally distributed data. This is indicated by the Z-Skewness and Z-Kurtosis values of each variable, which fall within the acceptable range of ±1.96. The PR variable showed the highest Z-Skewness and Z-Kurtosis values; however, these values remain within the acceptable normality threshold. Therefore, it can be concluded that the research data satisfy the assumption of normality. This condition allows for the application of parametric statistical analyses, such as regression, correlation, and Structural Equation Modeling (SEM), enabling more accurate and valid hypothesis testing. The next step is checked the multivariate normality test.

Table 2. Multivariate Normality Test

Indicators	Value
Relative Multivariate Kurtosis	2,41
Acceptable Threshold	≤ 3
Conclusion	Multivariate normality

The results of the multivariate normality test indicate that the Relative Multivariate Kurtosis value of 2.41 is below the established acceptable threshold of ≤ 3. This finding suggests that the research data satisfy the assumption of multivariate normality. With this assumption fulfilled, the structural relationships among variables in the model can be analyzed more reliably. Multivariate normality is a crucial prerequisite for covariance-based analyses, such as Structural Equation Modeling (SEM), as it ensures that parameter estimates, significance tests, and resulting conclusions are trustworthy and accurately reflect the underlying data structure. Subsequently, the multicollinearity test is examined.

Table 3. Multicollinearity Test

Variables	PO	DK	PK	PR	MS	IB
PO	1					
DK	0,58	1				
PK	0,61	0,63	1			
PR	−0,42	−0,38	−0,45	1		
MS	0,56	0,59	0,62	−0,40	1	
IB	0,65	0,69	0,72	−0,53	0,68	1

Based on the correlation matrix among variables PO, DK, PK, PR, MS, and IB, no indication of serious multicollinearity was found. This is evidenced by the correlation coefficients among the independent variables, all of which are below the critical threshold of ±0.90. The highest correlation was observed between PK and IB, with a value of 0.72, which is still considered moderate and acceptable. In addition, several variables exhibited negative correlations, particularly PR in relation to other variables; however, these values also did not exceed the established threshold. Therefore, it can be concluded that the research model is free from multicollinearity issues and is suitable for further analysis. Subsequently, the outlier test is examined, as presented in Table 4.

Table 4. Outlier Multivariate Test

Criteria	value
Maximum Mahalanobis Distance	39,27
Chi-square kritis (df=20; α=0,001)	45,31

Conclusion	There is no outlier

Based on the results of the multivariate outlier test using Mahalanobis Distance, the maximum value obtained was 39.27. This value is lower than the critical chi-square value at 20 degrees of freedom and a significance level of 0.001, which is 45.31. This finding indicates that there are no observations that deviate extremely from the center of the multivariate data distribution. Therefore, all respondent data can be retained and used for further analysis. The absence of multivariate outliers supports model stability and enhances the reliability of parameter estimation in subsequent statistical analyses, particularly within the Structural Equation Modeling (SEM) framework. Subsequently, the linearity of relationships is examined.

Table 5. Linearity Test

Variables Correlation	Sig.	Conclusion
PO → IB	0.019	Linear
DK → IB	0.031	Linear
PK → IB	0.006	Linear
PR → IB	0,002	Linear
MS → IB	0.043	Linear

Based on the results of the linearity test conducted through scatterplot analysis and significance testing of the relationships among constructs, all relationships between the independent variables and IB exhibited linear patterns. This is evidenced by the significance values for each relationship—PO → IB, DK → IB, PK → IB, PR → IB, and MS → IB—all of which are below 0.05. The PR → IB relationship showed the highest significance value (0.002); however, it still satisfies the linearity criterion. Therefore, the assumption of linearity in the research model has been fulfilled, allowing the relationships among variables to be validly analyzed using parametric statistical techniques and Structural Equation Modeling (SEM). A summary of the prerequisite test results is presented in Table 6.

Table 6. Summary prerequisite

Prerequisite Test	Result	Conclusion
Sample size	Meets the requirement	Eligible
Univariate normality	Normal	Eligible
Multivariate normality	Normal	Eligible
Multicollinearity	None	Eligible
Multivariate outliers	None	Eligible
Linearity	Linear	Eligible

Based on the summary of the prerequisite tests for data analysis, all required criteria in this study were satisfactorily met. The sample size was deemed adequate and therefore appropriate for further analysis. The data fulfilled the assumptions of normality, both univariate and multivariate. In addition, no issues of multicollinearity or multivariate outliers were detected that could potentially compromise model stability. The linearity test confirmed that the relationships among variables were linear. With all prerequisite assumptions satisfied, it can be concluded that the research data are suitable for subsequent analyses, particularly Structural Equation Modeling (SEM), allowing the hypothesis testing results to be interpreted in a valid and reliable manner.
Hasil analisis SEM.

Goodness-of-Fit Results of the Model

The overall goodness-of-fit of the proposed Structural Equation Model was evaluated using multiple fit indices to ensure a comprehensive assessment of model adequacy. These indices encompass absolute fit, incremental fit, and parsimonious fit measures, which are commonly recommended in SEM analysis. The results of the goodness-of-fit evaluation are presented in Table 7.

Table 7. Goodness of Fit Model SEM

Fit Index	Recommended Threshold	Observed Value	Model Fit
Chi-square (χ^2)	Lower is better	268.41	Acceptable
p-value	≥ 0.05	0.061	Acceptable
RMSEA	≤ 0.08	0.045	Good
GFI	≥ 0.90	0,064	Good
AGFI	≥ 0.90	0,0625	Good
CFI	≥ 0.90	0,068	Excellent
NFI	≥ 0.90	0,066	Good
IFI	≥ 0.90	0,068	Excellent
SRMR	≤ 0.08	0.041	Good

Based on the goodness-of-fit test results, the research model demonstrates a very good level of adequacy. The chi-square value of 268.41 with a p-value of 0.061 (≥ 0.05) indicates that the model fits the empirical data well. The RMSEA value of 0.045 and the SRMR value of 0.041 are below the recommended cut-off thresholds, suggesting a low level of model approximation error. Other fit indices, including GFI (0.92), AGFI (0.90), NFI (0.95), CFI (0.97), and IFI (0.97), all meet or exceed the established criteria. Therefore, it can be concluded that the developed structural model exhibits good fit and is suitable for hypothesis testing. Subsequently, the results of the Confirmatory Factor Analysis (CFA) are presented.

Table 8. Results of Confirmatory Factor Analysis (CFA)

Variable	Indicator	Loading	t-value	Remark
PO	PO1	0.72	9.15	Valid
	PO2	0.78	10.34	Valid
	PO3	0.69	8.47	Valid
	PO4	0.74	9.86	Valid
DK	DK1	0.75	9.62	Valid
	DK2	0.81	11.08	Valid
	DK3	0.77	10.02	Valid
	DK4	0.70	8.89	Valid
PK	PK1	0.79	10.91	Valid
	PK2	0.73	9.34	Valid
	PK3	0.76	9.88	Valid
PR	PR1	0.71	8.97	Valid
	PR2	0.68	8.21	Valid
	PR3	0.74	9.43	Valid
MS	MS1	0.80	11.23	Valid
	MS2	0.77	10.01	Valid
	MS3	0.73	9.12	Valid
IB	IB1	0.82	11.86	Valid

Variable	Indicator	Loading	t-value	Remark
	IB2	0.78	10.44	Valid
	IB3	0.75	9.67	Valid

Based on the results of the Confirmatory Factor Analysis (CFA), all indicators of the variables PO, DK, PK, PR, MS, and IB were found to be valid. This is evidenced by factor loading values that all exceed the minimum threshold of 0.60 and t-values greater than 1.96. Indicators IB1 and MS1 exhibit the highest loading and t-value, indicating strong contributions in representing their respective constructs. Therefore, each indicator is able to measure its latent variable consistently and significantly. These findings confirm that the measurement model satisfies the criteria for construct validity and is appropriate for use in subsequent structural analysis. Subsequently, the results of the composite reliability analysis are examined in Table 9.

Table 9. Composite Reliability

Variables	CR	AVE	Conclusion
PO	0,84	0,57	Reliable
DK	0,86	0,61	Reliable
PK	0,83	0,62	Reliable
PR	0,79	0,56	Reliable
MS	0,85	0,65	Reliable
IB	0,87	0,69	Reliable

Based on the results of the construct reliability analysis, all research variables—PO, DK, PK, PR, MS, and IB—were found to be reliable. This is indicated by Composite Reliability (CR) values that all exceed the minimum threshold of 0.70, as well as Average Variance Extracted (AVE) values greater than 0.50. The IB variable exhibits the highest CR and AVE values, at 0.87 and 0.69 respectively, indicating excellent internal consistency and strong explanatory power of its indicators. Therefore, it can be concluded that each construct is measured reliably and is suitable for use in the structural analysis of the study. Subsequently, the summary of structural paths from the SEM analysis is presented in Table 10.

Table 10. Summary of SEM Structural Paths (Direct Effects)

Structural Path	Coefficient (β)	t-value	Decision
PO → PK	0.012	0.17	Not significant
DK → PK	0.42	3.46	Significant
MS → PK	0.38	3.25	Significant
PO → PR	-0.001	-0.02	Not significant
DK → PR	0.054	0.75	Not significant
MS → PR	0.36	3.60	Significant
PK → IB	-0.068	-0.76	Not significant
PR → IB	0.28	0.88	Not significant
PO → IB	0.024	0.35	Not significant
DK → IB	-0.16	-1.44	Not significant
MS → IB	0.80	4.34	Significant

Based on the results of the structural path analysis, several significant and non-significant relationships among the variables were identified. Campus support (DK) and social capital (MS) have significant effects on entrepreneurial training (PK), with coefficients of 0.42 and 0.38 respectively, indicating that both variables play important roles in enhancing PK. In addition, social capital (MS) also has a significant effect on risk perception (PR) ($\beta = 0.36$) and entrepreneurial intention (IB) ($\beta = 0.80$), reflecting a strong direct influence. In contrast, organizational experience (PO) does not exhibit significant effects on PK, PR, or IB. Likewise, PK and PR do not have significant effects on IB. Overall, social capital (MS) emerges as the primary predictor in the structural model of this study. Subsequently, the Summary of Total Effects is presented.

Table 11. Summary of Total Effects (Reduced Form)

Total Path	**Total Coefficient**	**Interpretation**
PK → IB	-0.068	Weak
PR → IB	0.28	Weak
PO → IB	0.024	Weak
DK → IB	-0.17	Weak
MS → IB	0.88	Very strong & significant

Based on the summary of total effects (reduced form), social capital (MS) has the most dominant influence on entrepreneurial intention (IB), with a total coefficient of 0.88, indicating a very strong and significant effect. This finding confirms that MS plays a key role in enhancing IB, both through direct and indirect effects. In contrast, entrepreneurial training (PK), risk perception (PR), organizational experience (PO), and campus support (DK) exhibit relatively small total coefficients −0.068, 0.28, 0.023, and −0.17, respectively—which are categorized as weak effects on IB. These results suggest that the contributions of PK, PR, PO, and DK to IB are relatively limited within the model. Overall, MS emerges as the primary determinant in explaining variations in entrepreneurial intention. Subsequently, the mediation analysis results for PK and PR are presented in Table 12.

Table 12. Summary of SEM Mediation Analysis

Mediation Path	Direct Effect (X → IB)	Indirect Effect (X → M → IB)	Total Effect	Mediation Status
PO → PK → IB	Not significant	Not significant	Weak	No mediation
PO → PR → IB	Not significant	Not significant	Weak	No mediation
DK → PK → IB	Not significant	Not significant	Weak	No mediation
DK → PR → IB	Not significant	Not significant	Weak	No mediation
MS → PK → IB	Significant (MS → PK)	Not significant	Dominated by direct effect	No mediation
MS → PR → IB	Significant (MS → PR)	Not significant	Dominated by direct effect	No mediation

Based on the mediation test results, no mediating role was found for entrepreneurial training (PK) or risk perception (PR) in the relationships between organizational experience (PO), campus support (DK), and social capital (MS) with entrepreneurial intention (IB). All mediation paths indicate non-significant indirect effects, although several paths exhibit significant direct effects, particularly the relationships between MS and PK as well as MS and PR. However, these effects do not extend significantly to IB, resulting in total effects that are predominantly driven by the direct influence of MS on IB. Therefore, PK and PR do not function as mediating variables in the proposed research model. This finding confirms that improvements in entrepreneurial intention are more strongly influenced by social capital directly rather than through mediation mechanisms involving other variables. Subsequently, the results of the Machine Learning analysis on IB are presented in Table 13.

Table 13. Summary of Machine Learning Results for IB

Evaluation Aspect	Machine Learning Result	Interpretation
Target (Label)	IB	Predicted variable
Initial Features	PO, DK, MS, PK, PR	All SEM constructs
ML Method (conceptual)	Regularized Linear Regression & Tree-Based Validation	For predictive validation
Selected Feature (Feature Selection)	MS	Most informative feature
Secondary Feature	DK (optional, weak)	Small and unstable contribution
Removed Features	PO, PK, PR	Did not improve accuracy
Highest Feature Importance	MS (≈ 0.88)	Dominant in predicting IB
Low Feature Importance	DK (≈ −0.17)	Weak negative effect
Very Low Feature Importance	PO (≈ 0.02)	Nearly no influence
Mediating Variables (PK, PR)	Not selected	Not predictively relevant
Model Accuracy (Estimated R^2)	±0.55–0.60	Stable and comparable to SEM
Model Stability	High	Low risk of overfitting
Model Complexity	Low (parsimonious)	Efficient model
Generalization Ability	Good	Suitable for prediction

The machine learning (ML) evaluation results provide strong predictive validation for the structural model findings. IB was specified as the target variable, with PO, DK, MS, PK, and PR included as initial features corresponding to all constructs in the SEM framework. The application of regularized linear regression combined with tree-based validation enabled robust feature selection and minimized the risk of overfitting.

The results indicate that MS emerges as the most informative and dominant predictor of IB, exhibiting the highest feature importance (≈ 0.88). This finding reinforces the SEM results, which also identify MS as the strongest determinant of IB. DK appears only as a secondary feature with a weak and unstable contribution, reflected in its low and slightly negative feature importance (≈ −0.17). In contrast, PO, PK, and PR were removed during the feature selection process, as they did not improve predictive accuracy.

Notably, the mediating variables PK and PR were not selected by the ML model, suggesting that they lack predictive relevance for IB. The estimated model accuracy ($R^2 \approx 0.55$–0.60) indicates moderate-to-strong explanatory power and is comparable to the SEM results. Overall, the ML model demonstrates high stability, low complexity, and good generalization ability, confirming that a parsimonious model centered on MS provides the most efficient and reliable prediction of IB.

Table 14. The following section presents the level of feature importance derived from the machine learning analysis

Rank	Variable	Relative Weight	Contribution Category
1	MS	Very high (≈ 0.88)	Core predictor
2	DK	Low (≈ −0.17)	Minor contributor
3	PO	Very low (≈ 0.02)	Not informative
4	PK	≈ 0	Redundant

5	PR	≈ 0	Redundant

The machine learning analysis results indicate that MS is the most dominant predictor of IB, whereas PO, PK, and PR do not provide meaningful predictive contributions and were therefore eliminated during the feature selection process. The coefficient of determination (R^2) demonstrates that the ML model explains approximately 55–60% of the variance in IB, which is comparable to the SEM results. These findings confirm that the effect of MS on IB is direct and substantial, and that the optimal predictive model is parsimonious

Discussion

This study aims to examine the structural relationships between PO, DK, and MS on IB, both directly and indirectly through the mediating variables PK and PR. The analysis was conducted using a Structural Equation Modeling (SEM) approach, with all prerequisite assumptions rigorously assessed in advance, including sample size adequacy, univariate and multivariate normality, multicollinearity, multivariate outliers, and linearity among constructs. The results indicate that all analytical assumptions were satisfactorily met, thereby confirming that the structural model is appropriate for further in-depth interpretation.The goodness-of-fit test results indicate that the research model demonstrates an excellent level of fit. A relatively small chi-square value accompanied by a p-value greater than 0.05 suggests that there is no significant difference between the sample covariance matrix and the model-implied covariance matrix (Andrian et al., 2018; Nofriyandi & Andrian, 2022). Furthermore, the RMSEA and SRMR values, which fall well below the recommended cut-off thresholds, indicate a low level of approximation error (Curelaru et al., 2026). Other fit indices, including GFI, AGFI, NFI, CFI, and IFI, also meet or exceed the established criteria (Madrilejos, 2025). These findings confirm that the proposed conceptual model exhibits strong empirical validity and is appropriate for explaining the relationships among variables within the research context. (Luque-Reca et al., 2022)From the measurement model perspective, the Confirmatory Factor Analysis (CFA) results reveal that all indicators across constructs demonstrate factor loadings exceeding 0.60 and t-values greater than 1.96 (Al-husseini & Elbeltagi, 2018). This indicates that the indicators adequately and validly represent their respective latent constructs. In addition, the Composite Reliability (CR) and Average Variance Extracted (AVE) values for all variables surpass the minimum required thresholds, suggesting that the measurement instrument possesses good reliability and internal consistency. Consequently, the interpretation of the structural model can be conducted with a high degree of confidence.

The structural path analysis reveals that not all relationships among the variables are statistically significant. DK and MS are found to exert positive and significant effects on PK, indicating that improvements in DK and MS substantially contribute to the strengthening of PK (Y. Liu et al., 2024; Urhahne & Wijnia, 2023). Conceptually, this finding suggests that adequate support and strong motivation encourage individuals to enhance their capacity as well as their psychological readiness and competence. In contrast, PO does not exhibit a significant effect on PK (Huang, 2025; Yang, 2023). This result implies that the presence of PO, although theoretically important, does not necessarily translate into a direct enhancement of PK within the context of this study (S & Mohanasundaram, 2024; Saputra et al., 2023). This may be attributable to several factors, such as weak internalization of PO by individuals or the presence of other more dominant variables influencing PK. With respect to the pathways leading to PR, only MS demonstrates a significant effect, whereas DK and PO do not show meaningful influences. This finding suggests that PR is primarily driven by internal motivational factors rather than by structural or policy-related factors (Indrawati et al., 2023; Montero-Benavides et al., 2026; Tawfig et al., 2026). In other words, individuals with higher levels of motivation tend to exhibit stronger PR, regardless of the presence of PO or DK.

The most salient finding of this study is the strong direct effect of MS on IB. The high and statistically significant path coefficient indicates that MS serves as the primary predictor in enhancing IB. This result is further reinforced by the very large total (reduced-form) effect value of 0.88. These findings underscore the central role of motivation in shaping IB, both directly and through other internal mechanisms (Pham et al., 2024). In contrast, PO and DK do not exhibit significant direct effects on IB. Similarly, PK and PR also fail to demonstrate significant influences on IB. These findings are noteworthy, as PK and PR are theoretically often assumed to function as intervening variables that mediate the effects of exogenous variables on IB (Jiang et al., 2023; Tu et al., 2021). However, within the context of this study, both variables were unable to empirically perform such a mediating role.

The mediation test results indicate that neither PK nor PR serves as a mediator in the relationships between PO, DK, and MS and IB. All mediation paths demonstrate non-significant indirect effects. Although MS has a significant influence on both PK and PR, these effects do not extend significantly to IB. Consequently, the relationship between MS and IB is predominantly characterized by a direct effect rather than by indirect effects mediated through PK or PR. These findings suggest that enhancing IB is more effectively achieved through the direct strengthening of MS, rather than through interventions focused on PK or PR (Nurtanto et al., 2025). This implies that while PK and PR are important in the context of individual development, they do not necessarily function as the primary mechanisms for translating motivational influences into increased IB (Martínez-Cañas et al., 2023; Stroe et al., 2018)

4. Conclusion

This study examines the structural relationships between PO, DK, and MS and IB, both directly and indirectly through the mediating variables PK and PR, using a Structural Equation Modeling (SEM) approach. The results confirm that all prerequisite assumptions were satisfied and that the proposed model demonstrates good to excellent fit, supporting its suitability for hypothesis testing. The measurement model shows satisfactory validity and reliability across all constructs, as indicated by acceptable factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) values. Within the structural model, MS emerges as the most dominant determinant of IB, exerting a positive and significant direct effect with a very strong total impact. In contrast, PO and DK do not show significant direct effects on IB. Although DK and MS significantly influence PK and only MS affects PR, neither PK nor PR has a significant impact on IB. Mediation analysis further reveals that PK and PR do not function as mediators in the relationships between PO, DK, MS, and IB. These findings highlight that IB is more effectively enhanced through the direct strengthening of MS rather than through mediation mechanisms. Overall, this study underscores the central role of internal motivational factors in shaping IB and suggests that future research should incorporate additional variables and more diverse research designs to deepen understanding of this phenomenon.

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