

# Rethinking Entrepreneurship Education Policy Mandates to Foster Resilient Student Startup Ecosystems in Indonesia

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## Research Article

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# Abstract

This study evaluates ecosystem predictors of student business sustainability in a college setting. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (MGA), this study analyzes empirical data from 1,032 student entrepreneurs to compare how these predictors operate across different Regional Minimum Wage (UMR) clusters. The results of the structural equation modeling analysis indicate that actual execution capabilities, specifically entrepreneurial competence and business acumen, are the only significant drivers of business sustainability. Conversely, institutional support, motivational factors, and entrepreneurship awareness campaigns did not show a statistically significant impact on actual business survival. Furthermore, the MGA analysis confirmed the presence of structural invariance among these regional economic clusters, indicating that nominal regional economic disparities do not moderate these structural pathways. These findings challenge the common assumption that regional economic conditions determine the survival of student startups and demonstrate that the operational requirements for business viability are universal. Therefore, universities and policymakers need to shift from mass motivational campaigns focused on quantity and meeting basic awareness quotas toward the creation of a rigorous, standardized, and real-world experience-based ecosystem for technical skills development.

## Introduction

Fostering student entrepreneurship at universities is a strategic goal of higher education aimed at enhancing innovation and economic growth globally. Higher education institutions have established a robust entrepreneurial ecosystem by integrating business incubators and specialized curricula to cultivate a business mindset among students (Caratozzolo et al., 2026; Kato, 2025). As a result of these institutional investments, students are reported to have a very strong intention to become entrepreneurs, which serves as a critical cognitive predictor of future business activities (Saoula et al., 2023). Consistent with this, various empirical models of student entrepreneurship indicate that cognitive intent to become an entrepreneur explains approximately 47% of the variance in students' initial business interest (Lyu et al., 2023). In the context of developing countries, these systems often rely on experience-based learning models, external capital and resources (Kato, 2025), and active alumni mentoring networks (Maki & Miyachi, 2011) to help students transition from classroom concepts to active market observation.

Despite high levels of motivation among college students, the transition from entrepreneurial intent to actual business execution remains a significant challenge for the majority of college students. Globally, student startups experience an extremely high failure rate, with studies indicating that often more than 80% of student-led startups collapse in the early stages of operation (Sholikhah et al., 2025). Conversely, the success rate of these startups is very low, with fewer than 2% of student-led startups surviving to achieve long-term commercial viability and financial sustainability (Lagrazon et al., 2026; Nadan, 2014; Zhang, 2015). This significant gap between intention and execution is highlighted by various cases in an international context. For example, the higher education ecosystem in Switzerland reports an

entrepreneurial intention rate of 18.8%, yet only a small fraction of these students successfully transition into active companies with steady revenue (Köhle & Birkenmeier, 2023). This gap stems from a combination of various structural barriers, including limited seed capital, a lack of financial literacy, inadequate mentoring, and an unsupportive macroenvironment (Bailey, 2025; Baquirin et al., 2025; Chavis et al., 2012; Gál, 2017 ).

In Indonesia, the global push to foster student entrepreneurship has been integrated into top-down national education policies. Under the “Impactful Campus” initiative, the Ministry of Higher Education, Science, and Technology has shifted the evaluation of higher education institutions from traditional administrative input-based measurements toward outcome- and impact-based metrics. This policy is reinforced through Key Performance Indicators, under which universities are encouraged to prioritize producing graduates who actively create jobs, including through independent businesses. These regulations have evolved from Ministry of Education and Culture Regulation No. 754/P/2020 to Ministry of Education, Culture, Research, and Technology Regulation No. 210/M/2023 and Ministry of Higher Education, Science, and Technology Regulation No. 358/M/KEP/2025. This policy mandates that universities meet graduate outcome targets across various categories of institutional performance (Sebayang et al., 2024). Achieving these targets carries significant financial implications, as a university’s performance score is directly linked to the allocation of operational funding and incentives from the government (Sebayang et al., 2024). At the macroeconomic level, these institutional performance requirements serve as a key strategic instrument for increasing the nation’s overall entrepreneurship rate, with the aim of realizing the “Golden Indonesia 2045” vision.

To ensure that student startups represent truly independent ventures, the Indonesian government has implemented a strict financial threshold (Handayati et al., 2021). Under ministerial regulations, a student startup is officially recognized as an active entrepreneur at a university only if the business generates a monthly income of at least 1.2 times the regional minimum wage (UMR). (Prasetyo & Hoesin, 2022) However, this universal threshold creates regional inequities across the country, given the differences in the nominal UMR across regions (Pratomo et al., 2024). Universities in metropolitan areas face higher revenue targets compared to regions with lower UMRs, leading to potential disparities in institutional performance rankings (Doh et al., 2025). While some public universities with well-established business incubators and consistent tracking systems have been able to meet these targets, many others report failure due to limitations in tracking student business data (Sebayang et al., 2024). To mitigate this decline in performance, the Indonesian government has implemented targeted assistance programs, such as the Student Entrepreneurship Strengthening Program and the Merdeka Entrepreneurship Program, which serve as incubators capable of helping students build financially successful businesses (Sebayang et al., 2024).

However, an environment with such rigid policies reveals a critical research gap. A profound disparity exists between students’ entrepreneurial intentions and knowledge and the actual viability of their businesses as measured by various mandated financial metrics. The contradiction between high psychological readiness and low levels of actual business execution has been documented in previous

literature as a phenomenon in which students are overly confident in their operational capabilities, ultimately failing to transition into financially sustainable companies (Alam et al., 2025; Al-Hattami, 2025; Harima et al., 2021; Harima & Harima, 2024; Lestari et al., 2025; Mina-Raiu & Oprescu, 2026; Narmaditya et al., 2026; Nungsari et al., 2023; Sulistyowati et al., 2026; Utama et al., 2019; Zhou et al., 2026). This gap arises because traditional higher education curricula focus too heavily on theoretical business structures, such as guiding students to design business model canvases for academic assessment, but have failed to establish a functional skills ecosystem with practical financial literacy and strong capital support. This issue leaves student startups vulnerable to immediate failure due to a lack of seed capital and capital protection.

More importantly, the Indonesian government's top-down regulation requiring companies to achieve monthly revenue targets of 1.2 times the minimum wage directly conflicts with the life cycle of a startup. In entrepreneurship theory, the first 1 to 3 years of a company represent a phase known as the "Valley of Death" (Zapata-Molina et al., 2025), during which founders typically adopt a capital-burning strategy by reinvesting all net revenue back into business operations and limiting their personal take-home pay to ensure cash flow stability. Under the KPI framework, such promising startups are at risk of being deemed failures. While previous research has explored students' entrepreneurial intentions, a significant gap remains regarding understanding how student entrepreneurs can navigate this transition to achieve the income required by regulatory standards under various constraints.

To address this gap, this study examines the specific impact of the policy mandating an income of 1.2 times the regional minimum wage on student startups. The novelty of this study lies in its evaluation of the practical effects generated by top-down financial standards and key performance indicators, rather than on the general characteristics of the startups themselves (Albornoz & Mundaca, 2026). Evaluating this specific policy is crucial for understanding how universities' key performance indicators influence the survival strategies of student startups, more specifically, regarding the strategic adjustments required to navigate the "Valley of Death" (Somia et al., 2024). The objective of this study is to reconstruct the university's skills ecosystem by identifying specific pedagogical, technological, and structural needs to help achieve these financial targets. This study addresses the following research questions: First, how does the regulation requiring monthly income of 1.2 times the regional minimum wage affect the operational resilience and strategic decisions of student startups? Second, what primary structural and resource-based components of the university's skills ecosystem are needed to help student startups transition from mere psychological readiness to financial sustainability in the real world?

## Methodology

This section will describe the research design, participant characteristics, measurement instruments, translation process, and statistical analysis framework used to examine the relationship between students' business readiness and the prevailing monthly income standards in Indonesia.

# Research Design and Participants

This study employs a quantitative cross-sectional design to provide a comprehensive assessment of students' business readiness and real-world business execution. The cross-sectional survey design is recognized as a robust and efficient approach for evaluating entrepreneurship programs in higher education, as it allows us to examine psychological readiness, institutional variables, and real-world business outcomes simultaneously within a single observation period (Oftedal et al., 2018; Xianchao & Yanbo, 2024). This design provides a reliable foundation for examining the complex relationships among students across the country. The population of this study consists of higher education students in various provinces across Indonesia. The final sample comprised 1,032 university students. This large sample size is statistically robust, satisfies the need for representativeness in sampling, and provides the statistical power required to conduct complex multivariate analyses, confirmatory factor analyses, and Structural Equation Modeling (SEM) (Khoshi et al., 2018; Vuković, 2024).

## Measurement and Instrument

This study used 73 items from a validated scale adapted from Panakaje et al. (2026) to evaluate startup readiness. All missing item codes (such as AW5 or PT5) were intentional and reflect items that were eliminated during the factor reduction process. The survey is divided into two sections: a demographic profile section and a multidimensional psychological readiness assessment. The demographic section of the instrument is designed to capture respondents' backgrounds and categorize the status of their startups, thereby creating an integrated profile narrative. In this regard, D1 (Age) categorizes respondents into four age intervals: 18–20 years, 21–23 years, 24–26 years, and 27 years or older, which helps identify generational groups. D2 (Gender) records respondents as female or male to evaluate potential gender disparities in the resilience of student startups. Geographic parameters were also used via D3 (Province of Origin) and D4 (Regency/City of Origin), which identified the respondents' regional backgrounds. This geographic mapping is important for controlling the regional minimum wage (UMR) level. Additionally, D5 (Study Program & Faculty) captures students' study programs and disciplinary affiliations.

Most importantly, D6 (Business Category) serves as an evaluative measure of the 1.2-times-UMR revenue requirement by categorizing respondents' business operational stages into four levels: (1) Students who have not yet launched a venture and remain at the cognitive or ideation stage; (2) Students with early-stage, experimental ventures that operate with unpredictable monthly revenues; (3) Students with stable businesses whose net monthly income falls short of the local minimum wage baseline; and (4) students with highly viable, self-sustaining ventures that meet or exceed the official minimum wage standard. By linking the categorical data to the minimum wage database, the D6 measure serves as a dependent variable to analyze which factors successfully predict alignment with the government's performance indicators.

The second part of the measurement instrument assesses business readiness across nine psychological and institutional dimensions, using a four-point Likert scale ranging from 1 (Strongly Disagree) to 4 (Strongly Agree).

1. **Entrepreneurial Ability (EA1–EA18)**: This dimension assesses entrepreneurial self-confidence and practical execution skills. It measures the ability to generate new business ideas (EA1), set prices (EA4), use digital marketing platforms for branding (EA11), and solve technology-related problems (EA18).
2. **Business Acumen (BA1–BA13)**: This dimension assesses psychological resilience, adaptability, and emotional intelligence. The items focus on facing challenges (BA1), taking initiative without direction (BA5), remaining calm during uncertainty (BA9), and emotional regulation in team environments (BA11).
3. **Institutional Efforts (IE1–IE14)**: This dimension evaluates the role of support provided by the university and academic systems. It measures the impact of experiential learning (IE1), startup-focused courses (IE2), guidance from study programs (IE3), and encouragement to participate in business incubators (IE11).
4. **Motivational Factors (MF1–MF8)**: This dimension measures the push and pull motivators behind business ambitions. It evaluates wealth creation (MF6), personal development (MF5), and the drive to reduce community unemployment (MF7).
5. **Opportunity Factors (OF1–OF7)**: This dimension measures the ability to recognize opportunities. Key items measure the translation of innovative ideas into new ventures (OF2), the use of social networks to identify market gaps (OF3), and strategic planning (OF7).
6. **Socio-Cultural Factors (SCF1–SCF7)**: This dimension captures social capital and external environmental support. It assesses having a family business (SCF1), accessing seed capital through family (SCF4), and being influenced by social media (SCF7).
7. **Awareness (AW1–AW6)**: This dimension measures students' conceptual and ethical understanding. It evaluates their awareness of key entrepreneurial concepts (AW1), current market trends (AW2), and the business ethics required for consumer protection (AW6).
8. **Personality Traits (PT1–PT6)**: This dimension measures stable psychological traits. The key items are openness to exploring new business ideas (PT1), confidence in public speaking (PT4), and coping with negative emotions (PT6).
9. **Resources (R1–R5)**: This dimension evaluates the capacity to mobilize resources. The items in this dimension measure the ability to create intellectual property (R1), organize physical resources (R2), access financial support (R3), recruit human resources (R4), and coordinate technical resources (R5).

To ensure construct equivalence and linguistic validity, the survey instrument underwent a cross-cultural adaptation and a forward-backward translation process (Norambuena-Paredes et al., 2026). The original English survey items were translated into Indonesian by two independent bilingual native Indonesian speakers. A third independent language expert corrected minor inconsistencies to refine the draft of the Indonesian-language instrument. The draft was then back-translated into English by two bilingual

researchers who had not been exposed to the original English questionnaire. The back-translated items were compared with the original source to make conceptual and semantic adjustments, ensuring that the standardized scale is appropriate for the context of higher education in Indonesia (Norambuena-Paredes et al., 2026).

## Data Analysis

Statistical analysis for this study was conducted in two steps to transition from preliminary data preparation to structural path modeling. Partial Least Squares Structural Equation Modeling (PLS-SEM) offers superior predictive power and greater flexibility when analyzing complex multidimensional models, as well as when exploring relationships involving categorical dependent variables, such as business outcome levels (Dash & Paul, 2021; Vukovi'c, 2024). The data was then divided into two consecutive phases using IBM SPSS Statistics 26 and SmartPLS 4.

Preliminary data screening, descriptive demographic profiling, and Exploratory Factor Analysis (EFA) were conducted using IBM SPSS Statistics 26 (Farradonna et al., 2023). Descriptive statistics were then calculated to map demographic background variables and to determine the underlying distribution for business categories (D6). EFA was conducted to assess the underlying factor structure of the adapted survey items and to verify the suitability of the sample (Yu et al., 2026). The suitability of the correlation matrix for factor extraction was evaluated using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity.

Table 1  
Kaiser-Meyer-Olkin and Bartlett's Test of Sphericity Results

| Statistical Test              | Metric                          | Empirical Value |
|-------------------------------|---------------------------------|-----------------|
| Kaiser-Meyer-Olkin Measure    | Sampling Adequacy Value         | 0.972           |
| Bartlett's Test of Sphericity | Approx. Chi-Square ( $\chi^2$ ) | 44,143.284      |
|                               | Degrees of Freedom (df)         | 3,160           |
|                               | Significance (p-value)          | < .001          |

## Source: Primary Data, processed (2026)

The results in Table 1 show that the KMO sampling adequacy index of 0.972 is above the threshold of 0.80, indicating an adequate level of sampling for structural factor extraction (Yu et al., 2026). Furthermore, Bartlett's test of sphericity is highly significant, with an estimated Chi-Square ( $\chi^2$ ) value of 44,143.284 (df = 3,160, p < 0.001), confirming that the correlation matrix is factorable and that the items share sufficient common variance to proceed with the structural model evaluation.

## Findings

# Spatial, Socio-Cultural, and Operational Typologies of Student Startup Survival

To evaluate the operational impact of standardized regulations across different regions, a bivariate crosstabulation analysis was conducted on students’ business categories (D6) across three minimum wage (UMR) clusters (High, Medium, and Low UMR regions). Table 2 shows the frequencies and percentages (% within UMR Cluster) for 1,032 respondents.

Table 2  
Crosstabulation of Regional UMR Clusters and Student Business Categories

| Regional UMR Cluster    | Metric           | Ideation (No business yet; Level 1) | Experimental (Unstable revenue; Level 2) | Stable (Below UMR; Level 3) | Self-Sustaining (Above UMR; Level 4) |
|-------------------------|------------------|-------------------------------------|------------------------------------------|-----------------------------|--------------------------------------|
| High UMR Region         | Count            | 73                                  | 28                                       | 9                           | 3                                    |
|                         | % within Cluster | 64.6%                               | 24.8%                                    | 8.0%                        | 2.7%                                 |
| Medium UMR Region       | Count            | 52                                  | 38                                       | 24                          | 13                                   |
|                         | % within Cluster | 40.9%                               | 29.9%                                    | 18.9%                       | 10.2%                                |
| Low UMR Region          | Count            | 586                                 | 146                                      | 41                          | 19                                   |
|                         | % within Cluster | 74.0%                               | 18.4%                                    | 5.2%                        | 2.4%                                 |
| Total                   | Count            | 711                                 | 212                                      | 74                          | 35                                   |
|                         | % within Cluster | 68.9%                               | 20.5%                                    | 7.2%                        | 3.4%                                 |
| Chi-Square Test Results | Value / df       | ( $\chi^2$ ) = 74.698               | df = 6                                   | p < .001                    | Cramer's V = 0.190                   |

Source: Primary Survey Data (2026).

The Pearson chi-square test of independence confirmed a highly significant statistical relationship between students’ UMR clusters and their business categories ( $\chi^2 = 74.698$ , df = 6, p < 0.001). The Cramer’s V coefficient of 0.190 indicates a moderate effect size, confirming that the geographic location of startups represents a critical external factor in determining compliance with regulations.

The data reveals a stark regional disparity in policy compliance. Student startups operating in the Medium UMR region exhibit the highest operational mobility, accounting for the largest proportion of stable and self-sustaining businesses. In contrast, startups in the High UMR region face various administrative challenges. While most of these startups are able to establish stable operations, they remain stuck with revenues below the UMR standard. This pattern indicates that, from this perspective, an increase in the UMR acts as a systemic barrier to the further development of student startups. Meanwhile, the Low UMR region is characterized by obstacles where the majority of students fail to carry out active operations and remain stuck in the ideation phase, with only a small fraction of this group able to establish self-sustaining companies.

An ordinal logistic regression analysis was conducted to evaluate the influence of demographic characteristics—specifically, UMR cluster, age, and gender—on the probability that students would be involved in higher-category startup businesses. Before determining the individual parameter estimates, the overall performance of the model was evaluated using standard goodness-of-fit and diagnostic measures. Table 3 outlines the model fitting statistics and pseudo R<sup>2</sup> indices.

Table 3  
Model Fit and Diagnostic Summary Metrics for Ordinal Logistic Regression

| Diagnostic Metric     | Parameter / Index                             | Empirical Value | Hypothesis Test (df) | Significance (p) |
|-----------------------|-----------------------------------------------|-----------------|----------------------|------------------|
| Model Fitting         | -2 Log Likelihood                             | 204.468         |                      |                  |
|                       | Likelihood Ratio Chi-Square (X <sup>2</sup> ) | 113.776         | df = 6               | < .001           |
| Pseudo R <sup>2</sup> | Cox and Snell Coefficient                     | 0.104           |                      |                  |
|                       | Nagelkerke Coefficient                        | 0.126           |                      |                  |
|                       | McFadden Coefficient                          | 0.062           |                      |                  |
| Model Specification   | Link Function                                 | Logit           |                      |                  |
|                       | Valid Sample Size (N)                         | 1,032           |                      |                  |

Source: Primary Data, processed (2026).

As shown in Table 3, the likelihood ratio test comparing the final model to the intercept-only baseline was highly significant, indicating that the demographic variables significantly improved the model’s predictive power. The Nagelkerke pseudo R<sup>2</sup> coefficient indicates that the predictors explain approximately 12.6% of the variance in the ordinal business outcome, satisfying the diagnostic threshold for nonparametric behavioral models. With the model’s adequacy established, individual parameter estimates were calculated to identify the direction and strength of each predictor. Table 4 presents the

cumulative regression coefficients (B), standard errors, Wald statistics, and confidence intervals for each threshold and predictor location.

Table 4  
Parameter Estimates for Ordinal Logistic Regression on Student Business Survival

| Parameter                  | Estimate<br>(B) | Std. Error<br>(SE) | Wald   | df | Sig.<br>(p) | 95% Confidence Interval |             |
|----------------------------|-----------------|--------------------|--------|----|-------------|-------------------------|-------------|
|                            |                 |                    |        |    |             | Lower Bound             | Upper Bound |
| Threshold (Cut-off)        |                 |                    |        |    |             |                         |             |
| [Business Category = 1.00] | -0.417          | 0.621              | 0.452  | 1  | .502        | -1.634                  | 0.800       |
| [Business Category = 2.00] | 1.061           | 0.621              | 2.914  | 1  | .088        | -0.157                  | 2.279       |
| [Business Category = 3.00] | 2.359           | 0.631              | 13.962 | 1  | < .001      | 1.122                   | 3.597       |
| Location (Predictor)       |                 |                    |        |    |             |                         |             |
| [UMR_Cluster = 1] (High)   | 0.356           | 0.213              | 2.803  | 1  | .094        | -0.061                  | 0.773       |
| [UMR_Cluster = 2] (Medium) | 1.391           | 0.187              | 55.281 | 1  | < .001      | 1.024                   | 1.758       |
| [UMR_Cluster = 3] (Low)    | 0 <sup>a</sup>  | .                  | .      | 0  | .           | .                       | .           |
| [Age = 1.00] (18–20 Years) | -1.822          | 0.619              | 8.669  | 1  | .003        | -3.035                  | -0.609      |
| [Age = 2.00] (21–23 Years) | -0.878          | 0.621              | 2.002  | 1  | .157        | -2.094                  | 0.338       |
| [Age = 24–26 Years]        | -0.773          | 0.775              | 0.995  | 1  | .319        | -2.293                  | 0.746       |
| [Age = 27 Years & Above]   | 0 <sup>a</sup>  | .                  | .      | 0  | .           | .                       | .           |
| [Gender = 1.00] (Male)     | 0.082           | 0.143              | 0.330  | 1  | .566        | -0.198                  | 0.363       |
| [Gender = 2.00] (Female)   | 0 <sup>a</sup>  | .                  | .      | 0  | .           | .                       | .           |

Source: Primary Data, processed (2026).

## Note

Link function: Logit. 0<sup>a</sup> This parameter is set to zero because it is redundant.

The regression location metrics reveal distinct and divergent predictive behaviors among the demographic covariates. Gender does not represent a significant predictor in student startup business processes, as the comparison between females and males yields an insignificant Wald statistic. This indicates that the operational effects of the minimum wage regulation are still considered egalitarian with respect to gender. Conversely, age group exhibits a critical predictive boundary. Being in the youngest student group (ages 18–20) significantly reduces the log-odds of operating in the advanced business category compared to the older age group (ages 27 and up), while this negative impact becomes statistically insignificant for the 21–23 and 24–26 age groups.

In addition, the minimum wage cluster emerged as a very strong predictor of business operations. Operating in regions with a medium minimum wage significantly increases the likelihood of startup survival compared to regions with a low minimum wage, whereas the predictive difference between regions with a high minimum wage and those with a low minimum wage did not reach statistical significance.

To map a hierarchical typology of student startup survival based on demographic and geographic predictors, we conducted a Classification Tree analysis using the Chi-squared Automatic Interaction Detection (CHAID) algorithm with a maximum tree depth parameter of 3. This non-parametric decision tree model progressively divided the 1,032 respondents into subgroups based on the statistical significance of their associations with the ordinal-scale business outcome category (D6). As illustrated in Fig. 1, the CHAID decision tree maps conditional probabilities and sequential decision rules that determine the survival of student startups, and illustrates the nonlinear interaction effects between age group, regional minimum wage target, and gender.

The primary structural split originating from Node 0 identified Age (D2) as the root predictor in the classification tree, which divided the sample into Node 1 and Node 2. The youngest age group, consisting of students aged 18 to 20 (Node 2,  $n = 684$ ), faces the most significant operational barriers, with 75.4% of its members still stuck at the idea stage (Level 1). In contrast, the older age group, which includes students aged 21 and older (Node 1,  $n = 348$ ), exhibits a much broader operational distribution as well as further business progress at higher levels.

Among these branches, the CHAID algorithm identified Node 4 as the most optimal business sustainability profile across the entire sample. This subgroup consists of students aged 21 and older who run businesses in regions with a moderate minimum wage. At Node 4, student entrepreneurs achieved the highest comparative performance, with 20.4% successfully reaching the self-sufficient stage (Level 4) and 24.1% running stable businesses but falling below the regional minimum wage threshold (Level 3). In contrast, the classification tree indicates severe structural barriers at Node 6, which represents the operational profile with the greatest limitations. This node includes student founders in the youngest age group (18 to 20 years old) located in metropolitan areas with high regional minimum wage (UMR) standards. For this specific subgroup, the success rate at the defined self-sufficiency stage (Level 4) was nonexistent (0.0%).

Finally, conditional gender differences were observed among the senior student group through the terminal split at the deepest level of the decision tree, represented by Node 8 and Node 9. This final split indicates that gender interactions depend on specific regional thresholds. Specifically, among the senior student group, male-led ventures (Node 8) showed a slightly higher proportion at the independent level (9.2%) compared to female-led ventures (Node 9), which recorded a Level 4 success rate of 2.9%.

## Multi-Dimensional Ecosystem Predictors of Venture Survival

Although the demographic and spatial typologies highlight the severe structural constraints imposed by regional minimum wage policies, they do not fully explain the internal mechanisms that enable certain student startups to survive the entrepreneurial “Valley of Death.” To answer the second research question, the PLS-SEM approach was used to map a multidimensional ecosystem, encompassing psychological readiness, institutional support, sociocultural capital, and resource mobilization, that drives actual business implementation. This PLS-SEM analysis was conducted in two systematic stages. First, the psychometric robustness of the measurement model was established, followed by an evaluation of the structural paths and their predictive relevance. The measurement model was evaluated to establish the reliability and validity of nine psychological and institutional latent constructs prior to testing the structural hypotheses. The evaluation of reflective constructs was conducted rigorously using PLS-SEM criteria.

Table 6  
Reflective Measurement Model Assessment: Reliability and Convergent Validity Results

| Latent Construct                      | Cronbach's Alpha | Composite Reliability (rho_a) | Composite Reliability (rho_c) | AVE   |
|---------------------------------------|------------------|-------------------------------|-------------------------------|-------|
| Ability                               | 0.931            | 0.938                         | 0.938                         | 0.461 |
| Acumen                                | 0.894            | 0.905                         | 0.909                         | 0.435 |
| Awareness                             | 0.845            | 0.865                         | 0.888                         | 0.614 |
| Institution                           | 0.908            | 0.919                         | 0.921                         | 0.496 |
| Motivation                            | 0.828            | 0.850                         | 0.863                         | 0.445 |
| Opportunity                           | 0.856            | 0.936                         | 0.876                         | 0.504 |
| Personality                           | 0.778            | 0.863                         | 0.825                         | 0.490 |
| Resources                             | 0.832            | 0.845                         | 0.880                         | 0.595 |
| Socio-Cultural                        | 0.819            | 0.844                         | 0.863                         | 0.482 |
| Source: Primary data processed (2026) |                  |                               |                               |       |

The results of the measurement model indicate high internal consistency reliability. Cronbach’s alpha values ranged from 0.778 to 0.931, and composite reliability ranged from 0.825 to 0.938; these figures comfortably exceed the standard threshold of 0.70 (Vuković, 2024). Regarding convergent validity, several constructs—specifically Ability (AVE = 0.461), Acumen (AVE = 0.435), Motivation (AVE = 0.445), Personality (AVE = 0.490), and Socio-Cultural (AVE = 0.482), exhibit AVE values slightly below the ideal threshold of 0.50. However, convergent validity is considered acceptable if the corresponding Composite Reliability (CR) value exceeds 0.70. Given that all of these constructs exhibit very high CR values (ranging from 0.825 to 0.938), the indicators share sufficient common variance, thereby confirming acceptable convergent validity for further structural analysis.

To demonstrate that each dimension reflects statistically distinct phenomena, discriminant validity was rigorously assessed using the Heterotrait-Monotrait Correlation (HTMT) ratio. HTMT is the modern standard for discriminant validity in composite model analysis, which requires that all inter-construct ratios be strictly below a conservative threshold of 0.90.

Table 7  
Heterotrait-Monotrait Ratio (HTMT) Discriminant Validity Matrix

| Latent Constrct                       | [1]   | [2]   | [3]   | [4]   | [5]   | [6]   | [7]   | [8]   | [9]   | [10] |
|---------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Ability                               | --    |       |       |       |       |       |       |       |       |      |
| Acumen                                | 0.857 | --    |       |       |       |       |       |       |       |      |
| Awareness                             | 0.710 | 0.745 | --    |       |       |       |       |       |       |      |
| Business Target                       | 0.303 | 0.275 | 0.183 | --    |       |       |       |       |       |      |
| Institution                           | 0.653 | 0.705 | 0.668 | 0.159 | --    |       |       |       |       |      |
| Motivation                            | 0.689 | 0.809 | 0.762 | 0.178 | 0.727 | --    |       |       |       |      |
| Opportunity                           | 0.662 | 0.764 | 0.755 | 0.146 | 0.632 | 0.866 | --    |       |       |      |
| Personality                           | 0.701 | 0.801 | 0.838 | 0.181 | 0.644 | 0.829 | 0.787 | --    |       |      |
| Resources                             | 0.772 | 0.732 | 0.729 | 0.271 | 0.590 | 0.684 | 0.644 | 0.773 | --    |      |
| Socio-Cultural                        | 0.618 | 0.605 | 0.615 | 0.209 | 0.580 | 0.627 | 0.558 | 0.584 | 0.724 | --   |
| Source: Primary data processed (2026) |       |       |       |       |       |       |       |       |       |      |

Nearly all construct pairs fall well below the conservative threshold of 0.85. Although the HTMT ratio between Motivation and Opportunity (0.866) slightly exceeds 0.85, this value remains well below the standard threshold of 0.90 (Henseler et al., 2015), confirming that the nine psychological dimensions and the business category targets are empirically distinct constructs.

After establishing construct validity and reliability, the structural model was evaluated to test the hypothesized relationships among multidimensional ecosystem predictors, control variables, and the ordinal outcome of business sustainability. The structural model showed a coefficient of determination ( $R^2$ ) of 0.188, indicating that the combination of psychological, institutional, and sociocultural factors, along with control variables, explained 18.8% of the variance in the students' business operational levels. To assess the statistical significance of the structural paths, a bootstrapping procedure using 5,000 subsamples was conducted. Parameter estimates, including beta ( $\beta$ ) values from the original sample and p-values, are presented visually in Fig. 2.

The structural evaluation revealed that, among the nine hypothesized ecosystem dimensions, only two constructs had a positive and statistically significant effect on the survival of student startups. Entrepreneurial competence emerged as a strong operational predictor ( $\beta = 0.201$ ,  $p < 0.001$ ), indicating that technical execution skills fundamentally determine business development. This is closely followed by business acumen ( $\beta = 0.129$ ,  $p = 0.008$ ). These results suggest that tangible operational competencies are the primary mechanism enabling student ventures to navigate the critical early stages. Additionally, the control variables indicate a significant demographic effect. Age has a positive effect on business survival ( $\beta = 0.257$ ,  $p < 0.001$ ), while the regional wage level (UMR cluster) shows a significant negative effect ( $\beta = -0.103$ ,  $p < 0.001$ ), further challenging the assumption that a metropolitan environment guarantees business success. Meanwhile, gender did not show a significant effect ( $\beta = 0.003$ ,  $p = 0.966$ ).

In contrast, the remaining seven dimensions, including resources ( $\beta = 0.073$ ,  $p = 0.103$ ), were unable to predict business survival, thereby revealing a crucial systemic misalignment within the university ecosystem. Most notably, institutional efforts yielded a non-significant structural path ( $\beta = -0.029$ ,  $p = 0.439$ ). This indicates that existing university incubators and curricular support have no impact on measurable business resilience. Furthermore, cognitive and psychological characteristics, such as motivation ( $\beta = 0.012$ ,  $p = 0.798$ ), personality ( $\beta = -0.017$ ,  $p = 0.671$ ), and awareness ( $\beta = -0.064$ ,  $p = 0.134$ ), were completely unable to predict operational financial viability. These structural barriers empirically confirm a phenomenon illustrating that high psychological readiness and theoretical knowledge are fundamentally very different from the harsh realities of market operations and compliance with revenue obligations set by the government.

To further investigate whether there are differences in structural relationships based on regional economic conditions, a Multi-Group Analysis (MGA) was conducted. The sample was divided into two distinct groups based on regional minimum wage levels: the High Regional Minimum Wage (UMR) cluster and the Medium Regional Minimum Wage (UMR) cluster. Figure 3 illustrates the differences in path coefficients between the two groups for the nine ecosystem predictors.

Visually, the bar chart displays varying degrees of coefficient shifts between the two groups. These differences range from a negative shift in the Motivation variable ( $\Delta\beta = -0.340$ ) to a positive shift in the Business Acumen variable ( $\Delta\beta = 0.229$ ). Negative values indicate slightly stronger structural paths in the

Medium Minimum Wage cluster, while positive values indicate stronger paths in the High Minimum Wage cluster. In addition to this visual representation, the details of the path coefficients for each regional cluster, along with their respective differences and MGA significance levels, are presented in Table 8.

Table 8  
Multi-Group Analysis (MGA) Results Comparing High and Medium UMR Clusters

| Variable                              | High UMR ( $\beta$ ) | Medium UMR ( $\beta$ ) | p-value (MGA) |
|---------------------------------------|----------------------|------------------------|---------------|
| Ability                               | 0.223                | 0.178                  | 0.624         |
| Acumen                                | 0.245                | 0.016                  | 0.115         |
| Awareness                             | -0.112               | -0.015                 | 0.512         |
| Institution                           | 0.034                | -0.135                 | 0.284         |
| Motivation                            | -0.175               | 0.165                  | 0.082         |
| Opportunity                           | 0.084                | 0.028                  | 0.741         |
| Personality                           | 0.031                | -0.16                  | 0.198         |
| Resources                             | -0.125               | -0.04                  | 0.605         |
| Socio-Cultural                        | -0.03                | -0.01                  | 0.902         |
| Source: Primary data processed (2026) |                      |                        |               |

As detailed in Table 8, the statistical bootstrapping method confirmed that none of the observed path differences reached the threshold for statistical significance. Thus, the analysis established the presence of structural invariance, indicating that the relationship between ecosystem predictors and student business sustainability remains consistent in both high-wage and medium-wage regions. The absence of significant variation indicates structural invariance across various regional clusters, which is a crucial finding. This demonstrates that the primary predictors of student business sustainability operate universally. The fundamental mechanisms required to sustain a business, specifically, tangible entrepreneurial skills and business acumen, are neither determined by nor superseded by the macroeconomic advantages of regions with higher wage levels. Concrete execution skills remain an absolute prerequisite, regardless of where the business operates.

## Out-of-Sample Predictive Power Assessment

To evaluate the generalization ability and practical applicability of the in-sample structural model, an out-of-sample predictive assessment was conducted using the PLS\_predict algorithm in SmartPLS 4. This procedure employs a tenfold cross-validation technique with ten iterations to assess whether the proposed structural pathways can predict outcomes for new, unobserved cases. This approach

mitigates the risk of overfitting and validates the practical utility of the behavioral model for forecasting at the policy level. Table 9 summarizes the predictive relevance and prediction error metrics, specifically, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), by comparing the PLS-SEM algorithm against the simple Linear Model (LM) and Interleaved Average (IA) benchmarks.

| Table 9<br>Out-of-Sample Predictive Performance (PLS_predict) Metrics for Student Business Survival |                |              |             |         |        |         |        |
|-----------------------------------------------------------------------------------------------------|----------------|--------------|-------------|---------|--------|---------|--------|
| Dependent Construct / Indicator                                                                     | Q <sup>2</sup> | PLS-SEM RMSE | PLS-SEM MAE | LM RMSE | LM MAE | IA RMSE | IA MAE |
| Business Target (D6)                                                                                | 0.166          | 0.705        | 0.539       | 0.727   | 0.555  | 0.772   | 0.621  |

Source: *Primary Survey Data, processed (2026).*

As shown in Table 9, the out-of-sample cross-validation assessment confirms that the structural model has robust predictive power. The primary target construct has a positive value, thereby meeting the basic diagnostic threshold required to establish out-of-sample validity. This positive value indicates that the structural model produces predictions that outperform the simple average of the unobserved cases.

To determine the appropriate level of predictive power, the prediction errors generated by the PLS-SEM structural model were directly compared with those from the simple LM (linear model) benchmark. The evaluation revealed a consistent pattern in which the PLS-SEM algorithm produced lower prediction errors on both primary metrics (RMSE and MAE) compared to the baseline linear model. When the PLS-SEM model produced lower prediction errors than the LM benchmark for all indicators of the target construct, it achieved the highest predictive power classification. Thus, the structural model was shown to have high predictive power, demonstrating its ability to accurately predict student business survival outcomes under the constraints of regional wage policies.

## Discussion

# The Primacy of Execution Skills over Policy-Driven Support

Empirical validation of “Entrepreneurial Competence” and “Business Acumen” as statistically significant primary predictors of student business success confirms that tangible operational capabilities are the true determinants of business viability. In youth entrepreneurship, student business founders often exhibit very high levels of cognitive intent, driven by academic programs and promotional curricula (Caratozzolo et al., 2026; Saoula et al., 2023). However, as demonstrated by Lyu et al. (2023), although cognitive intent explains most of the interest in the early stages, it does not automatically lead to the formation of an active business or business survival. This gap highlights an illusion in which high psychological self-efficacy and strong intentions actually mask critical deficiencies in the technical and practical skills needed to run a business in a competitive market (Farradinna et al., 2023; Hasan et al., 2026). The gap between theory and practice in entrepreneurship education also indicates that cognitive

intentions do not shield early-stage startups from harsh economic realities (Kozlinska et al., 2020; Rani & Ravi, 2026). Upon entering the market, student-run businesses face real and pressing challenges that demand concrete execution capabilities—such as aligning product-market fit, managing cost structures, and mitigating operational risks—rather than merely conceptual understanding (Corallo et al., 2019).

The operational reality of student-led startups in their early stages is characterized by extreme financial vulnerability and high failure rates; historical data show that the majority of such ventures fail to survive beyond their first few years due to a lack of capital and strategic errors (Jurgelevičius et al., 2025). This high failure rate stems from the fact that the real market acts as a harsh filter, rewarding only practical execution and cash flow management (Sarasvathy, 2008). Although entrepreneurship curricula generally place a strong emphasis on the development of business plans and theoretically static business models, they fail to replicate the dynamic environment with resource constraints that demands the application of an effectuation approach (Sarasvathy, 2008). In these highly uncertain situations, a business's survival is not determined by the founders' initial motivation, but rather by their practical ability to manage limited resources, iterate on business models amid financial pressure, and secure immediate cash flow (Corallo et al., 2019; Sarasvathy, 2008).

Conversely, the statistical insignificance of university-level institutional support, motivational factors, and entrepreneurial awareness in predicting startup success reveals a fundamental systemic misalignment. Most importantly, the lack of predictive power of university-level institutional support should not be viewed as an operational failure of the universities themselves, but rather as a systemic symptom of higher education policy at the macro level. Higher education institutions in Indonesia operate under strong coercive and normative pressures to align with the Merdeka Belajar-Kampus Merdeka (MBKM) framework, which mandates the implementation of standardized Key Performance Indicators (KPIs) across all public universities (Muttaqin, 2026). This top-down government mandate strongly encourages a focus on superficial, quantity-based metrics, such as the number of students participating in entrepreneurship activities or the number of registered startups, in order to secure government funding and maintain institutional prestige.

This administrative focus has pushed universities into a situation where institutional efforts are largely devoted to mass awareness campaigns, basic planning workshops, and credit-granting academic activities, rather than to in-depth, long-term business development (Mulyono et al., 2026). Furthermore, the rigid indicators set by the government, which require startups to generate revenue of at least 1.2 times the minimum wage, ignore financial realities as well as the natural growth patterns of early-stage businesses (Doh et al., 2025; Prasetyo & Hoesin, 2022). These rigid thresholds actually hinder sustainable, long-term business practices, given that early-stage ventures must prioritize reinvesting cash flow to ensure business survival rather than providing personal compensation to founders. By forcing universities to pursue standardized, instant financial milestones amid a highly unequal regional economic landscape, macro policies create counterproductive compliance pressures and actively hinder organic business growth (Pratomo et al., 2024; Harbindar Jeet Singh et al., 2026).

Ultimately, this policy framework has resulted in a severe gap, in which the state has succeeded in sparking initial entrepreneurial awareness and motivation but has left students without adequate structural support to survive in the real economy (Lestari et al., 2025). Although students were successfully encouraged or incentivized to start businesses to earn academic credit (Kirkwood, 2009; Panakaje et al., 2026), they often lacked the in-depth and ongoing professional mentoring, financial literacy, and direct capital protection necessary to scale up their operations (Ahsan et al., 2018; Wright et al., 2017). Traditional academic support systems, constrained by rigid semester schedules and classroom-based assessments, fail to provide the ongoing resources needed to mitigate the cash-draining cycles inherent in new ventures (Ahsan et al., 2018; Wright et al., 2017).

## **Structural Invariance: Debunking the Regional Economic Myth**

The MGA conducted to evaluate structural differences between regional clusters with high and medium minimum wages revealed an important finding: there were no statistically significant path differences ( $p > 0.05$ ) among the nine structural predictors, indicating structural invariance. This invariance indicates that the fundamental rules governing the survival of student startups are structurally consistent across various regional economic conditions. Whether student-led businesses operate in metropolitan centers with high wage levels or in regional markets with moderate wage levels, their chances of survival depend identically on the core competencies of “Entrepreneurial Ability” and “Business Acumen.” These findings align with the framework of structural consistency in the entrepreneurial ecosystem, which states that skill- and function-based performance remains an absolute operational determinant, regardless of the region’s external conditions (Ahsan et al., 2018; Corallo et al., 2019).

The implication of this structural invariance is that local economic wealth does not moderate the crucial relationship between execution skills and business survival. Although previous research on established university ecosystems has highlighted that the availability of external capital and high purchasing power can mitigate early-stage business risks (Wright et al., 2017), the results of our MGA analysis show that in developing economies, student-led startups are directly exposed to market forces without any buffers. This situation renders nominal regional economic differences insignificant when compared to the absolute need for operational capabilities. Essentially, operating in more affluent regions with high wage levels does not lower the threshold for the basic competencies required to manage cash flow, identify market demand, or achieve sustainable revenue (Farradinna et al., 2023; Sarasvathy, 2008). Consequently, student groups in regions with both high and moderate minimum wages face a similar reliance on the execution of applied technical business practices to prevent startup failure (Lyu et al., 2023).

Furthermore, these findings provide a strong empirical critique of the prevailing policy narrative regarding youth entrepreneurship. Policymakers often justify the extremely high failure rate of student startups, which frequently exceeds 80% by attributing it to macro-environmental constraints, such as low regional purchasing power, high local inflation, or poor regional economic infrastructure (Azeem et al., 2024;

Santisteban et al., 2022). This structural, fatalistic perspective shifts the focus of policy evaluation away from curriculum design toward unchangeable geographic conditions. However, the results of our MGA analysis directly debunk these regional economic myths. Statistical parity across structural pathways indicates that business failure is not an inevitable consequence of local minimum wage levels or macroeconomic conditions, but rather a direct reflection of a universal systemic deficit in practical, high-level execution skills (Muttaqin, 2026). Blaming macroeconomic conditions serves as an administrative defense that obscures pedagogical gaps and resource allocation problems within higher education institutions.

To bridge this implementation gap and support the sustainability of student-run businesses, a major paradigm shift in national policy is needed. Given that the structural factors determining business sustainability are constant across various regional wage levels, government practices that adjust expectations or set tiered performance benchmarks based on regional economic classifications are fundamentally flawed. Instead of altering expectations, the national education framework, such as the Merdeka Belajar-Kampus Merdeka (MBKM) program, must standardize rigorous, highly technical, and experience-based entrepreneurship training nationwide (Harun et al., 2020). This requires redirecting public funding away from mass entrepreneurship awareness campaigns and basic planning workshops. Instead, resources should be redirected to build a standardized support system focused on equity, one that provides direct capital assistance, advanced digital financial literacy, and ongoing professional mentoring across all regions (Singh et al., 2025).

## Conclusion

This study examines the structural and demographic determinants of the survival of student startups within Indonesia's highly competitive higher education policy environment. The findings indicate that long-term business survival is fundamentally determined by concrete execution competencies at the individual level, specifically, Entrepreneurial Competence and Business Acumen, while institutional support at the university level, motivational factors, and basic awareness do not have a statistically significant direct impact on operational success. Furthermore, MGA indicates the presence of full structural invariance between groups of students operating in regions with high and medium minimum wage standards. This statistical equivalence indicates that absolute reliance on practical execution skills, as opposed to institutional support that is merely formal in nature, is a universal mechanism that operates independently of local macroeconomic differences. This simultaneously refutes the assumption that a region's underlying economic conditions can serve as a buffer or alter the requirements for business survival.

These findings call for a significant paradigm shift in how government agencies and universities design and evaluate entrepreneurship policies for young people. Current national education mandates, such as the Merdeka Belajar-Kampus Merdeka (MBKM) framework, are heavily focused on quantitative Key Performance Indicators (KPIs); this has prompted public universities to divert resources toward mass entrepreneurship awareness campaigns, basic idea-development workshops, and the creation of short-

term, artificial student startups merely to meet administrative quotas. However, because these superficial activities generate only fleeting motivation without instilling tangible operational competencies, these efforts fail to bridge the crucial transition from mere intent to commercial viability. To address this policy gap, policymakers must shift from a quantity-oriented, administrative quota approach toward a resource allocation model that prioritizes quality. This transition requires rigorous, experience-based standardization of business training; the direct provision of seed capital; and the provision of ongoing professional mentoring designed to withstand the real-world cash flow cycles inherent in startup operations.

Although this structural model explains approximately 18.8% of the variance in students' business goals ( $R^2 = 0.188$ ), this coefficient represents a solid baseline. In the highly complex and multidimensional realms of human behavior, economic policy, and business sustainability, the ability to isolate nearly one-fifth of the variance using systematic ecosystem predictors provides a strong explanatory foundation. This focused isolation offers a clear empirical starting point by demonstrating that skill-based predictors remain highly stable. Future research should build upon these foundational findings by conducting longitudinal monitoring of students' entrepreneurial ventures to observe the long-term evolution of execution skills after graduation. In addition, researchers could explore the impact of external macroeconomic shocks on these structural relationships, or use phenomenological qualitative methods to examine in depth the microsociological processes through which student entrepreneurs acquire and refine their business acumen in real-world market situations.

## **Declarations**

## **Ethical approval**

The research protocol was approved by the Research Ethics Committee of Universitas Pendidikan Indonesia in accordance with the national guidelines and regulations for social science research.

### **Consent to participate**

Informed consent to participate in the study was freely given and obtained from all participants prior to data collection.

### **Consent to publish**

Not applicable.

## **Clinical trial number**

Clinical trial number: not applicable.

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# Author Contribution

Siti Nurbayani: Conceptualization, Writing – Original Draft (Introduction, Policy Review, Discussion, and Conclusion), Project Administration, Supervision, Writing – Review & Editing. Mokh. Iman Firmansyah: Methodology, Formal Analysis (PLS-SEM structural path modeling and Multi-Group Analysis), Software, Validation, Writing – Original Draft (Methodology and Statistical Results). Qolbi Mujahidillah Adzimat Sukmayadi: Investigation (data collection of the 1,032 student entrepreneurs), Resources, Data Curation, Visualization (tables and reflective model assessment), Writing – Review & Editing.

# Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

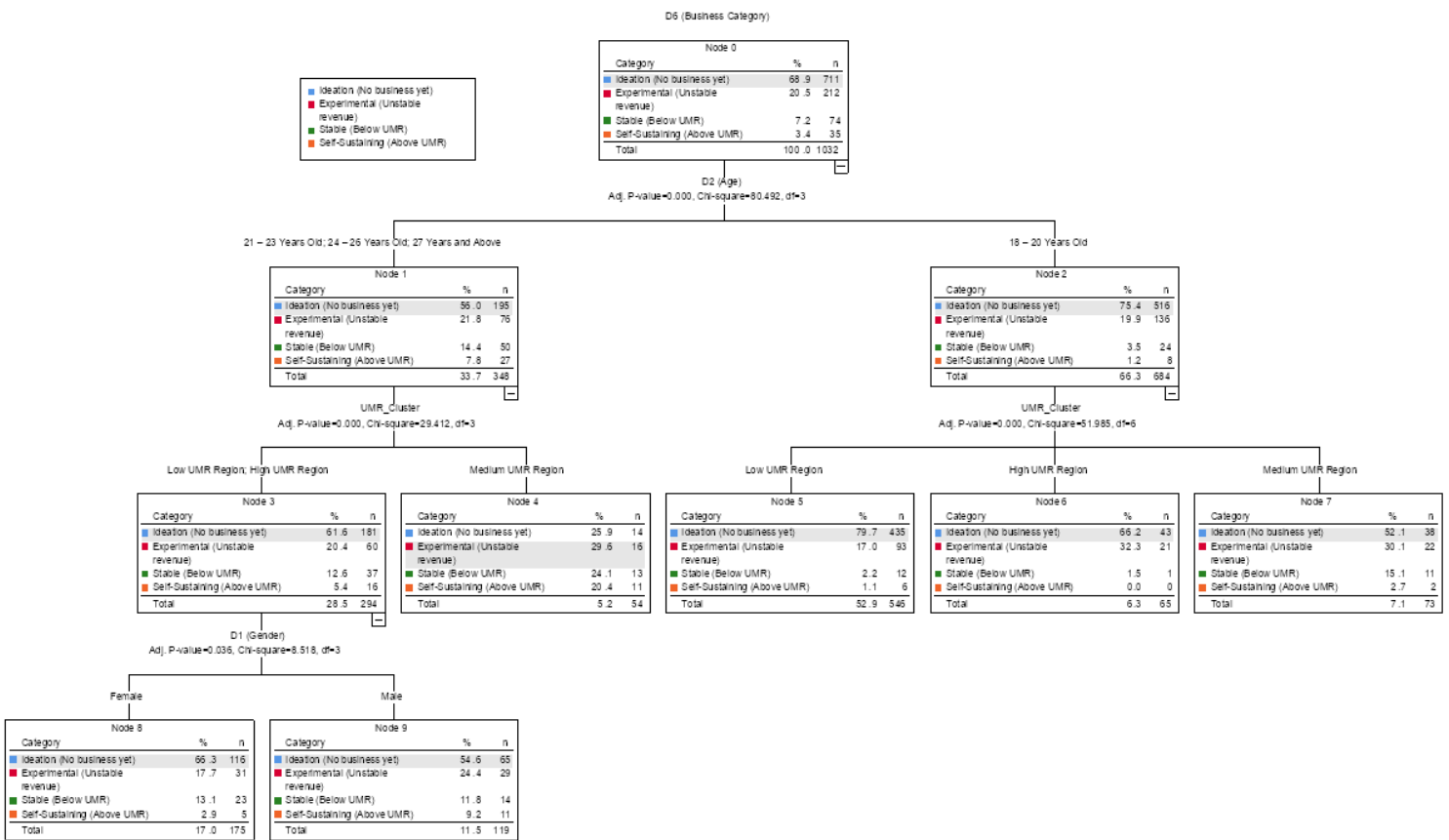


Figure 1

CHAID Decision Tree Empirical Model of Student Startup Survival Under Regional Minimum Wage Mandate

Source: Primary Data, processed (2026)

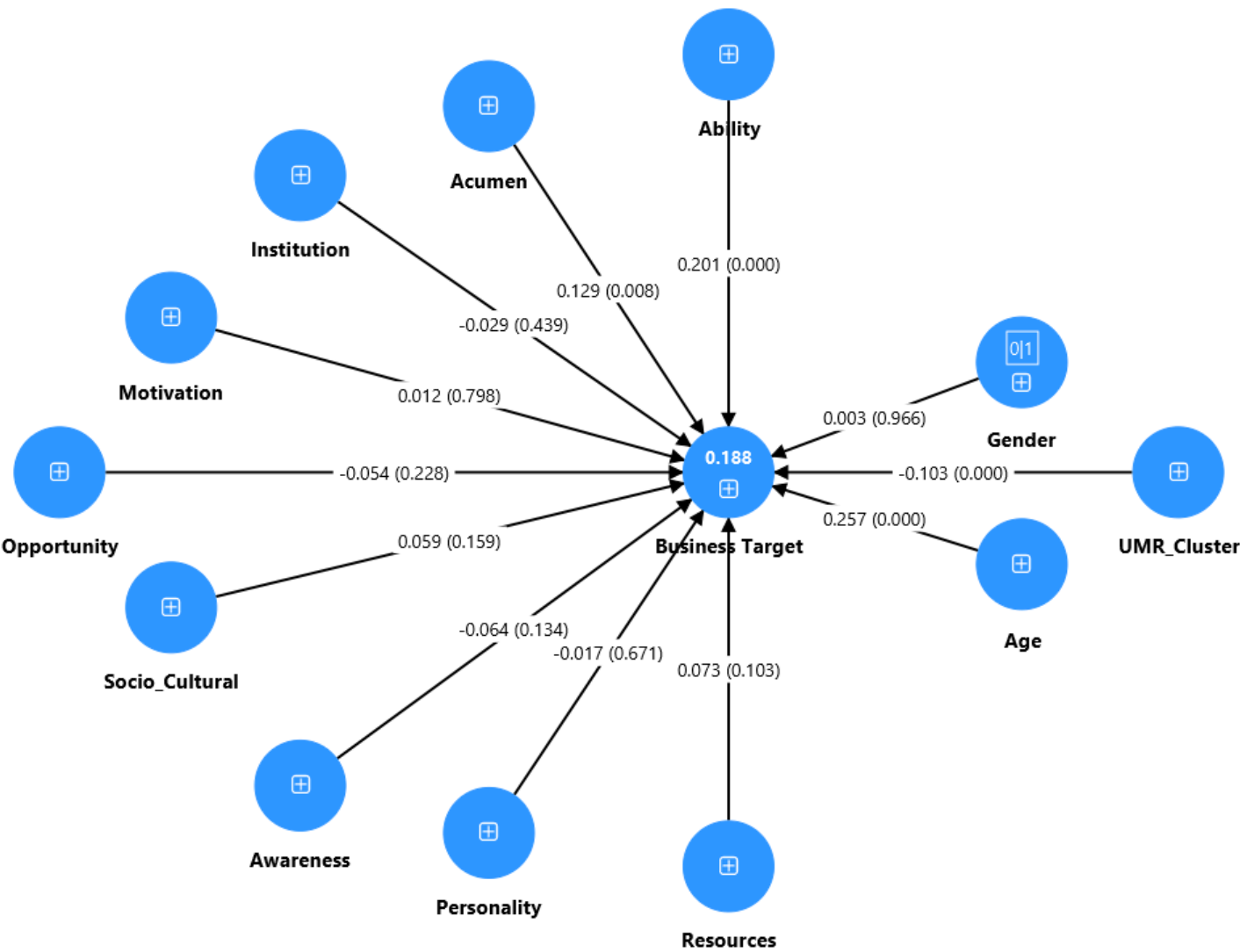


Figure 2

PLS-SEM Structural Model Assessment for Student Venture Survival

Source: Primary data processed (2026)

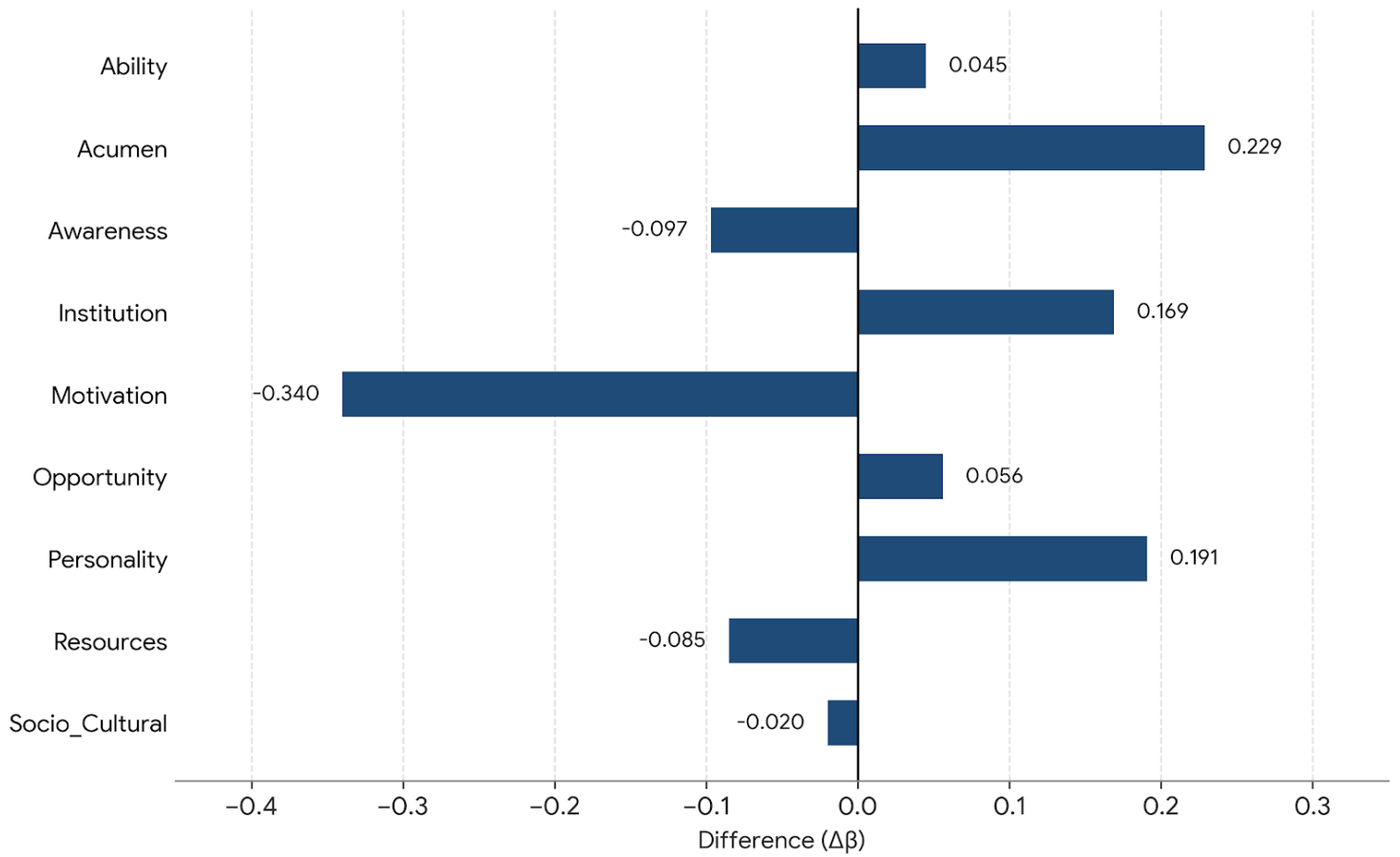


**Figure 3**

Path Coefficient Differences between High and Medium UMR Clusters

Source: Primary data processed (2026)