PREDICTING ENTREPRENEURIAL INTENTION AMONG COMPUTER SCIENCE STUDENTS USING STRUCTURAL EQUATION MODELING AND MACHINE LEARNING

BY

Abu Bakarr Sillah
ID: 242-25-021

This Report Presented in Partial Fulfillment of the Requirements for
The Degree of **Masters of Science in Computer Science and Engineering**

Supervised By

Dr. Sheak Rashed Haider Noori
Professor and Head
Department of CSE
Daffodil International University

Co-Supervised By

Dr. Arif Mahmud
Associate Professor and Associate Head
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Thesis titled "**Predicting Entrepreneurial Intention Among Computer Science Students Using Structural Equation Modeling and Machine Learning**", submitted by **Abu Bakarr Sillah, ID No: 242-25-021** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **13-09-2025**.

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Risk Management Division,
BRAC Bank Limited

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I hereby declare that this research has been done by me under the supervision of **Dr. Sheak Rashed Haider Noori, Professor and Head, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Dr. Sheak Rashed Haider Noori
Professor and Head
Department of CSE
Daffodil International University

Co-Supervised by:

Dr. Arif Mahmud
Associate Professor and Associate Head
Department of CSE
Daffodil International University

Submitted by:

Abu Bakarr Sillah
ID: 242-25-021
Department of CSE
Daffodil International University

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ABSTRACT

Entrepreneurial intention (EI) among students are critical drivers of innovation, job creation, and economic growth in contemporary societie. This study examines the determinants of entrepreneurial intention (EI) among computer science and engineering students in Bangladesh by integrating structural equation modeling (SEM) and machine learning (ML). Survey data were collected from 929 students. The reflective measurement model estimated in SmartPLS 4 demonstrated strong reliability and validity, while the structural model explained 57.2% of the variance in Entreprenuerial Intention.. Complementary ML models optimized through nested cross-validation, confirmed the robustness of findings, XGBoost yielded the lowest error (RMSE ≈ 1.00; R^2 ≈ .58. The integration of SEM and ML advances explanatory and predictive understanding of EI, suggesting that interventions should emphasize mastery-oriented training to enhance PBC, targeted knowledge development to strengthen EK, and orientation-building experiences to reinforce PA.

Keywords: entrepreneurial intention; computer science students; Bangladesh; PLS-SEM; machine learning; Theory of Planned Behavior; SHAP; importance-performance analysis.

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CHAPTER 1

CHAPTER 1 INTRODUCTION

1.1 Introduction

Entrepreneurial intention (EI) among university students has become an increasingly important topic in recent years, it is attracting attention from both researchers and policymakers [1]. This growing interest comes from the strong connection between EI and several key drivers of economic progress, such as innovation, job creation, and sustainable development. Universities are no longer seen today only as places where knowledge is shared, they also function as training grounds for entrepreneurial talent. Students are expected to develop the skills, confidence, and mindset needed to turn ideas into real ventures that can strengthen both personal and national economic resilience [2].

The university plays a very important role in shaping students' entrepreneurial intentions. It is a transitional period where young people begin forming their career goals, building specialized skills, and exploring possible paths into the workforce, either through traditional employment or by starting their own businesses. Because of this, EI is not just about personal success; it also influences broader socio-economic change by driving innovation, supporting new industries, and helping solve practical challenges [1]. Entrepreneurs introduce fresh ideas, creative solutions, and innovative products that address societal needs and push economies forward [3].

In this way, university students are considered a crucial group. Their exposure to higher education gives them not only technical knowledge but also the ability to analyze problems and adapt to new technological and market demands. Student-led entrepreneurship is increasingly viewed as a practical way to boost national competitiveness and promote sustainable development [4]. For developing economies especially, encouraging EI is seen as an important step to reduce unemployment and create a more inclusive, innovation-driven job market.

The importance of cultivating EI is especially noticeable in developing economies, where graduate unemployment and underemployment remain a very big issue [5]. In

Bangladesh, for example, almost 46% of university graduates encounter enough trouble in getting formal employment [5] In such contexts, entrepreneurship offers a practical option, making it possible for graduates to transition from job hunters to job developers. This process not only mitigates unemployment pressures but likewise fosters inclusive development through innovation-driven business and the development of chances across varied social groups. Finally, the cultivation of entrepreneurial culture within universities lines up carefully with more comprehensive worldwide agendas, particularly Sustainable Development Goal 8, which highlights the value of continual economic growth, efficient work, and decent work for youth [6] Embedding entrepreneurial education and support mechanisms in greater education institutions can enhance national entrepreneurial environments, gearing up graduates to generate endeavors, create work, and contribute meaningfully to socio-economic advancement. The study of EI amongst university students must be considered not only a crucial scholastic undertaking but also a useful necessary with considerable developmental implications.

The university is especially important for the formation of EI, as it represents a transitional period in which students form career goals, acquire specialized competencies, and start to assess paths toward future work or self-employment. Within this context, university students constitute a tactical group, as their exposure to greater education supplies both technical proficiency and analytical capability, allowing them to respond successfully to emerging technological and market obstacles. The research study of EI among university students should be considered not just a crucial academic undertaking however likewise a useful important with significant developmental ramifications.

The presence of engineering students presents a distinct population in college when analyzing entrepreneurial goal (EI) because their entrepreneurship orientation differs critically with the orientation of trainees in service or non-technical studies. Even though the literature demonstrates that entrepreneurship education is likely to stimulate entrepreneurial intent across academic fields, the effects of this type of education are not always of equal intensity or breadth in relation to their effects on entrepreneurial intent in engineering trainees [9] Among business students, the effect of such entrepreneurship education on entrepreneurial intent is often much more significant and pronounced. These conclusions indicate the need of discipline-based approaches to entrepreneurship education which entails engineering trainees are facilitated through intervention(s) which incorporate both their technical ability with the development of their entrepreneurial ability hence enabling them to transform the innovation potential into tangible entrepreneurial goals.

The use of theoretical aspects of view such as Theory of Planned Behavior (TPB) by Ajzen [10] provides further information about the predictors of entrepreneurial intention among engineering associates. Attitude towards entrepreneurship, subjective standards and viewed behavioral control (PBC) remain the focus of constructs that describe intent, although empirical evidence shows that their relative influence varies across disciplines [11] of the engineering population, personal mindset and PBC represent a significant share of intention. This suggests that entrepreneurial decision-making by engineering trainees should be better based on internal judgments of capacity and expediency as opposed to external social expectations. In addition to cognitive predictors, the characteristic and motivational factors also come into play in the establishment of entrepreneurial objective in the engineering trainees. The intent has a positive relationship with qualities like locus of control, self-efficacy, and need of accomplishment; however, these qualities interact differently with entrepreneurship education when compared to service analogs [12] In addition, the persistence of an objective action space among the engineering accomplices is present whereby high levels of entrepreneurial objective do not always translate into venture development. It has in fact been suggested that entrepreneurial motivation itself is an important moderating factor, explaining why intentions often remain latent in this group [13] [8].The utilisation of these variables in the framework of predictions would allow teachers to determine trainees with high entrepreneur potential as well as to design specific interventions that directly address their needs. High self-efficacy trainees but with relatively low direct exposure to business contexts may be served by defined mentorship programs or cross-disciplinary entrepreneurship classes. These predictive methods ensure that resources within an institution are assigned effectively, making the most out of them in as far as entrepreneurial development is concerned.

The predictive facet of EI also has more far-reaching strategic overtones on entrepreneurial and development contexts. Strong predictive designs can enable universities to study whether curricular changes, hackathons, or incubation activities are indeed enhancing entrepreneurial preparedness (Tu et al., 2019). Early identification of high-potential technopreneurs generates access to industry network and accelerators, venture capital investors in the early phases, thus hastening the lifecycle between the generation of principles and commercialization of the ideas in the market (Ewim, 2023). This way university settings can be turned into dynamic hubs of technological entrepreneurship, which will encourage the creation of ventures and contribute to the growth of the innovation-driven employment.

Policy wise, predictive models contribute to the ranking of investments in entrepreneurship education, research, and incubation centers at universities with the highest technopreneurial potential [15] By targeting resources in these these settings, there is improved likelihood of achieving transformational financial results. Notably, the consequences of such endeavors go far beyond the generation of start-up creators. An educated entrepreneurship that is informed by predictive insights can enhance graduate employability and build transferable skills that will have a longer shelf life and provide a competitive edge in volatile labour markets [16] These entrepreneur skills will be durable and flexible, adding longer-term value to predictive approaches to EI, as digitalization and automation continue to advance markets.

1.2 Motivation

Entrepreneurship is widely considered a required chauffeur of financial growth, development, and employment production particularly in the knowledge-driven economies. In the case of developing nations such as Bangladesh - where graduate unemployment remains a significant issue - encouraging entrepreneurship among university graduates has in fact become all the more critical. Despite the rapid growth of college, the labor market has failed to match the pace; underemployment and wasted human capacity has ensued. This shows the pressing necessity of providing the students with technical competence as well as an entrepreneurial frame of mind so that they could create opportunities themselves and contribute to the society.

In this context, the engineering and innovation trainees especially Computer Science and Engineering (CSE) have a special place. Their training helps them apply some of the emerging technologies like artificial intelligence, massive data, and cloud computing to create and create brilliant options high-growth startups. However, according to research study, engineering student is often less entrepreneurial-oriented than a service trainee showing a gap that needs a deeper analysis. The ability to determine the predictors of entrepreneurial intent (EI) among students of CSE, in turn, is critical to developing academic knowledge and guiding policy.

These results might help universities, policymakers and industry stakeholders to develop specific evidence-based policy initiatives to improve and develop communities of entrepreneurial frame of minds development. The main idea behind this research study is the dual problem of addressing graduate unemployment and at the same time helping the prospective technologists realize their entrepreneurial potential and contribute to sustainable financial transformation.

1.3 Research Objectives

The primary aim of this study is to predict entrepreneurial intention (EI) among Computer Science and Engineering (CSE) students through the application of machine learning techniques. To operationalize this aim, the study establishes the following specific objectives:

1. To assess the level of entrepreneurial intention among CSE students in selected universities in Bangladesh.
2. To examine the relationships between key psychological and contextual determinants—including attitude, subjective norms, perceived behavioral

control, entrepreneurial knowledge, personality traits, and innovation orientation and entrepreneurial intention.

3. To develop and validate a machine learning model capable of accurately predicting entrepreneurial intention among CSE students.
4. To identify the most influential predictors of entrepreneurial intention through feature importance analysis within machine learning algorithms.
5. To provide actionable recommendations for universities, educators, and policymakers on the design and implementation of targeted entrepreneurship programs for CSE students.

1.4 Research Questions

In alignment with these objectives, the study seeks to address the following research questions:

- What is the current level of entrepreneurial intention among CSE students in Bangladesh?
- How do psychological and contextual factors—such as attitude, subjective norms, perceived behavioral control, entrepreneurial knowledge, and personality traits—relate to entrepreneurial intention among CSE students?
- To what extent can machine learning techniques accurately predict entrepreneurial intention in this cohort?
- Which variables emerge as the strongest predictors of entrepreneurial intention within the machine learning model?
- How can the insights obtained from predictive modeling inform the development of effective entrepreneurship education programs and policy interventions tailored for CSE students?

1.5 Expected Output

The expected outcomes of this study are both theoretical and practical, contributing to entrepreneurship research and educational practice in meaningful ways:

1. Validated Measurement Model for Entrepreneurial Intention

   The study will provide a psychometrically sound measurement model for assessing entrepreneurial intention and its antecedents among CSE students. This includes evidence from exploratory and confirmatory factor analysis demonstrating construct validity and reliability.

2. Comprehensive Understanding of Predictors

   The research will identify the significant psychological and contextual determinants (such as attitude, subjective norms, perceived behavioral control, entrepreneurial knowledge, and personality traits) influencing entrepreneurial intention among CSE students in Bangladesh.

3. Predictive Machine Learning Model

   A robust machine learning-based predictive framework for entrepreneurial intention will be developed and validated. The model will demonstrate accuracy and reliability, enabling early identification of students with high entrepreneurial potential.

4. Feature Importance and Insights for Intervention

   The analysis will reveal which variables most strongly predict entrepreneurial intention, offering evidence-based guidance for educators and policymakers to design targeted entrepreneurship education programs for technical students.

5. Policy and Educational Recommendations

   The findings will lead to practical recommendations for universities and government bodies to foster an innovation-driven entrepreneurial ecosystem, thereby supporting Sustainable Development Goal 8 (Decent Work and Economic Growth).

6. Contribution to Literature

   This research will enrich the existing body of knowledge by integrating behavioral theory (Theory of Planned Behavior) with data-driven prediction models, offering a novel approach to studying entrepreneurial intention in technical disciplines.

1.6 Project Management and Finance

The research work doesn’t get fund from any individuals or organization.

1.7 Report Layout

The structure of this study is designed to provide a systematic and comprehensive presentation of the research process and findings. Chapter 1 offers an introduction to the study, outlining its aims, objectives, and principal research questions. Chapter 2 presents a critical review of the existing literature, summarizing key theoretical frameworks, empirical findings, and gaps that inform the current investigation. Chapter 3 provides a detailed description of the proposed methodology, including the research design, data collection procedures, and analytical techniques. Chapter 4 focuses on the presentation, analysis, and interpretation of the experimental results, highlighting key insights and patterns derived from the data. In Chapter 5, the study examines the broader implications of the findings, including the proposed Sustainability Plan, its societal and environmental impacts, and associated ethical considerations. Finally, Chapter 6 concludes the study by synthesizing the main findings, discussing their contributions to theory and practice, and outlining directions for future research initiatives.

CHAPTER 2
BACKGROUND

2.1 Preliminaries / Terminologies

Entrepreneurship is critical in generating innovation, employment, and economic development and hence the predominant subject of interest to institutions of higher learning in efforts to equip students with a fast-changing field of career development. In this framework, students of Computer Science and Engineering (CSE) constitute an exceptionally important group. Their technical skills in combination with knowledge of upcoming technology can put them in a distinctive position to undertake entrepreneurial ventures with enormous potential to have social and economic implications of significance to the society.

Nevertheless, the current studies show that CSE students tend to exhibit less entrepreneurial intentions than students of non-engineering fields. Most of them find it hard to turn their expertise into the entrepreneurial desire although they might be technically competent.

The latest developments of data-driven methods such as artificial intelligence (AI) and machine learning (ML) have allowed focusing on the main factors that influence entrepreneurial motivation in CSE students. The combination of those computing techniques will help to further enrich the comprehension of entrepreneurial behavior and suggest the evidence-based approach to developing innovation among this technically talented but under researched demographic.

2.2 Related Works

Many studies have been conducted to investigate entrepreneurial intentions in various fields, and many of them have identified a significant variation in the intention of engineering students in comparison to students of other institutions. Indicatively, a case study on 112 individuals established that engineering students tended to have low entrepreneurial ambitions as compared to non-engineer individuals. Interestingly, the attitudes towards entrepreneurship were not much different as per group but the difference was largely accredited to weak entrepreneurial mindsets among the engineering students.

The results highlight the need to enhance entrepreneurial thinking in the engineering education. Such characteristics like self-efficacy, risk-taking, and creativity were also reported to be key contributors to entrepreneurial ambition. The role of family, peers and mentors however seemed to be functioning differently to engineering students than the students in other fields, implying that contextual and cultural sources define the entrepreneurial motivations.

Continuing on this, a study involving 700 students used Partial Least Squares Structural Equation Modeling (PLS-SEM) and found out that entrepreneurial mindset, perceived behavioral control and personal interest negatively influenced entrepreneurial intention. On the other hand, the subjective norms of society or peer pressure revealed a negative correlation with the entrepreneurial motivation and the psychological well-being (e.g. autonomy) did not prove to have any significant impact.

Likewise, Sun et al. used chi-square tests, logistic regression and structural modeling to produce evidence that creativity and risk-taking have direct positive influences on entrepreneurial intention, but need for achievement and locus of control have indirect influences. Taken together, these works reiterate the fact that individual mindset is the most powerful predictor of entrepreneurial intention, and it is stronger than all the external factors, including the perceived opportunities or availability of resources..

In a different contribution, Pinto et al. [20] applied exploratory factor analysis and SEM to explore the intention to be an entrepreneur among engineering students by adopting proportionate stratified sampling. Their results revealed the joint impact of individual attributes, academic settings, and social settings on the entrepreneurial desires in students. However, unexpectedly, higher education itself found lesser direct effect implying the possibility that classroom-based interventions are not enough to drive entrepreneurial motivation.

Lastly, Belmonte et al. [21] concentrated on technopreneurial intentions in the field of engineering education. The study applied Pearson correlation and multiple regression analysis to determine that the influence of computer proficiency, previous entrepreneurial experience, and access to financial resources together explained 61.5% of the variation of the technopreneurial intentions. Surprisingly, entrepreneurial orientation which plays a critical role in other areas did not have a significant predictive value among students of engineering. This observation emphasizes the peculiarities of entrepreneurship motivation in technical education, which implies the necessity of individual solutions to stimulate entrepreneurial activities among the students of CSE.

Authors	**Focus/Insight**	**Method**	**Key Findings**
Arias and Flad [1]	Lower entrepreneurial intention among engineering students due to weaker entrepreneurial mindset.	Quantitative survey (N = 112)	Engineering students have similar attitudes as non-engineering peers but lower entrepreneurial intent.
Lei et al. [2]	Impact of personality, education, and social networks on entrepreneurial intentions.	Systematic literature review	Creativity, risk-taking, and self-efficacy significantly influence entrepreneurial intention.
Balgiu & Simionescu-Panait [3]	Examined psychological predictors such as attitude, perceived control, and curiosity among engineering students.	Online survey (N = 700); PLS-SEM	Attitude, perceived control, and curiosity positively influence intention; subjective norms negative.
Sun et al. [4]	Role of creativity, risk-taking, and motivational traits on entrepreneurial intention.	Chi-square test, Logistic Regression, SEM	Creativity and risk-taking have direct effects; need for achievement and locus of control indirect.
Nguyen et al. [5]	Determinants of entrepreneurial intention with mediating effects	Structural Equation Modeling (PLS-	Personal attitude is the strongest predictor; self-

	of self-efficacy.	SEM)	efficacy mediates personality effects.
Pinto et al. [6]	Influence of individual, academic, and social factors on entrepreneurial intention.	Proportionate stratified sampling, EFA, SEM	Academic education has minimal impact; social and individual factors play major roles.
Belmonte et al. [7]	Technopreneurial intention influenced by technology-related and resource-based factors.	Pearson Correlation, Multiple Regression	Computer ability, entrepreneurial experience, and access to capital explain 61.5% of intention.

2.3 Research Gap

In as much as past researchers have studied entrepreneurial intentions in engineering students, some of the gaps that may be critical have not been addressed. A lot of literature available in the field has the tendency to view engineering students as a homogenous group and does not make any distinction between more specific fields like Computer Science and Engineering (CSE). Nonetheless, CSE students have their own unique attributes, such as high level of technical knowledge, constant exposure to new technologies and being exposed to innovation climates. These qualities can affect their entrepreneurial actions in a different manner compared to students in other engineering fields (Belmonte et al., 2022).

In spite of this, little empirical investigation has been done specifically on the antecedents of entrepreneurial intention among CSE students or to compare their motivations with students of engineering in general. A contextual limitation is also present in most of the studies, with most of them being carried out in developed or Western economies (Arias and Flad, 2025; Pinto et al., 2024). With this geographical concentration, the countries such as Bangladesh have a great gap to stay up since the growth of the graduate unemployment and the boom in digital economy makes technopreneurship a more and more important channel to achieve economic growth.

There is not much known however about the ways in which in such contexts the culture, institutional structure and the limits that the resources provide inform entrepreneurship intentions. The lack of context-specific empirical evidence that takes into consideration these important factors, particularly with regard to CSE students is also a dearth.

The aim of this research is to fill these gaps by suggesting both psychological antecedents (e.g., attitudes, perceived behavioral control, and entrepreneurial orientation) and technological facilitators (e.g., innovation exposure and digital skills) that affect the entrepreneurial intentions of CSE students in Bangladesh. It is aimed at producing contextually relevant insights that may help in how policy decisions are made, curriculum development and ecosystem-building opportunities are created to achieve innovation and entrepreneurship.

2.4 Challenges

There are a number of both methodological and practical issues when studying the entrepreneurial intentions of CSE students. A significant challenge is finding a way to separate the influence of discipline-specific factors and more general, wide-based factors that influence entrepreneurial behavior. Although the Theory of Planned Behavior (TPB) offers a very effective theoretical background, the inclusion of other constructs like technological competence, exposure to innovation, and access to digital resources introduces complexities. It is difficult to form a holistic framework because there are no models that incorporate these variables.

The other major concern is that there is a scarcity of context-specific literature in the developing economies such as Bangladesh. Most of the available studies are based on the Western or highly industrialized world, so their results can never be universalized to the context that may be defined by peculiar cultural norms, institutional frameworks, and resource constraints. As a result, the adaptation of the existing theoretical frameworks is a matter that has to be considered closely regarding the local socio-economic conditions and the ecosystem of entrepreneurs.

There are also practical barriers that arise in the collection of data. The process of obtaining a sample that is large and representative can be difficult to navigate institutional permissions, across dozens of different academic units, and to keep participants involved. Also, response bias is also a factor of concern because students might report the socially desirable attitudes towards entrepreneurship and not provide their true intentions.

Lastly, the issue of technological competence cannot be measured, and it also adds complexity. As opposed to psychological structures that are well developed and have validated measurement scales there exists no standardized model on which to evaluate technology-related proficiency among CSE students. This would be difficult to measure using instruments that are not validated, which in turn would complicate the task of establishing the importance of technological expertise in influencing the entrepreneurial goals.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Proposed Methodology/Applied Mechanism

The Diagram 3.1 presents the methodological framework for predicting entrepreneurial intentions among Computer Science and Engineering (CSE) students.

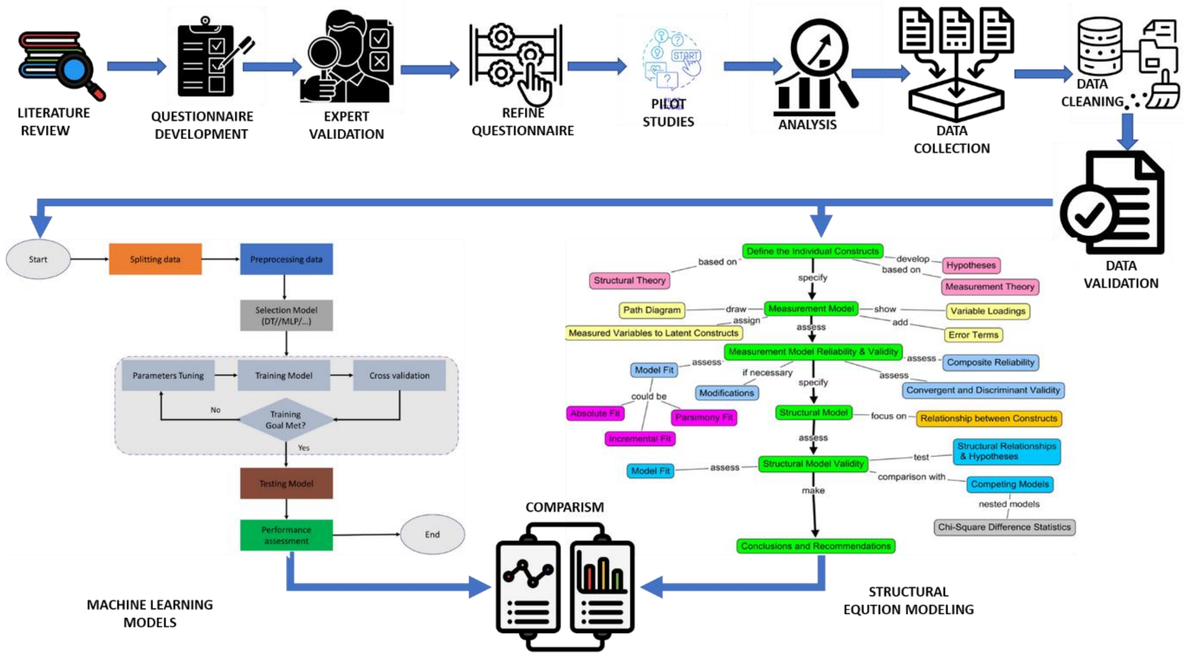

Figure 1: Methodology Flowchart

SEM is utilized to carefully evaluate hypotheses derived from established theories such as the Theory of Planned Behavior, making sure that relationships between variables are statistically confirmed and grounded in previous research study. In parallel, ML is used to discover hidden patterns and predictive relationships that traditional statistical methods may miss out on, thus complementing theory-bound constraints.

The research style is divided into 5 interconnected stages. The study develops and validates the research instrument-- a study capturing constructs like entrepreneurial mindset, viewed behavioral control, subjective standards, and technological proficiency. Reliability and material validity are thoroughly made sure for contextual suitability. Second, a pilot research study is carried out to identify weak points in the survey and improve the design prior to large-scale data collection. Third, information collection takes location using a tasting method that guarantees representativeness throughout Bangladeshi college while focusing on CSE students, provided their technological relevance. 4th, information cleansing and preprocessing are carried out to get rid of inconsistencies, missing values, and outliers, preparing the dataset for both SEM and ML analysis. The fifth phase includes analysis: SEM is applied to evaluate causal courses and theoretical designs, while ML is utilized to create predictive models that recognize the greatest predictors of entrepreneurial intent. By comparing the outcomes, SEM verifies theoretical relationships, while ML highlights prominent useful predictors, using an extensive, multidimensional understanding of CSE students' entrepreneurial intentions that bridges both theory and practice.

3.2 Instrument Development and Validation

3.2.1 Literature Review and Model Integration

An extensive systematic literature review was conducted to identify validated instruments related to entrepreneurial orientation, behavioral intention, and decision-making constructs. Three widely recognized theoretical models were integrated into a single measurement framework:

- Model 1: Theory of Planned Behavior (Ajzen, 1991)
- Model 2: Entrepreneurial Orientation Framework (Lumpkin & Dess, 1996)
- Model 3: Innovation Adoption or Risk Behavior Model

From these models, validated questionnaire items were extracted and combined to develop a comprehensive survey instrument. The integration process ensured that each construct was adequately represented and operationalized.

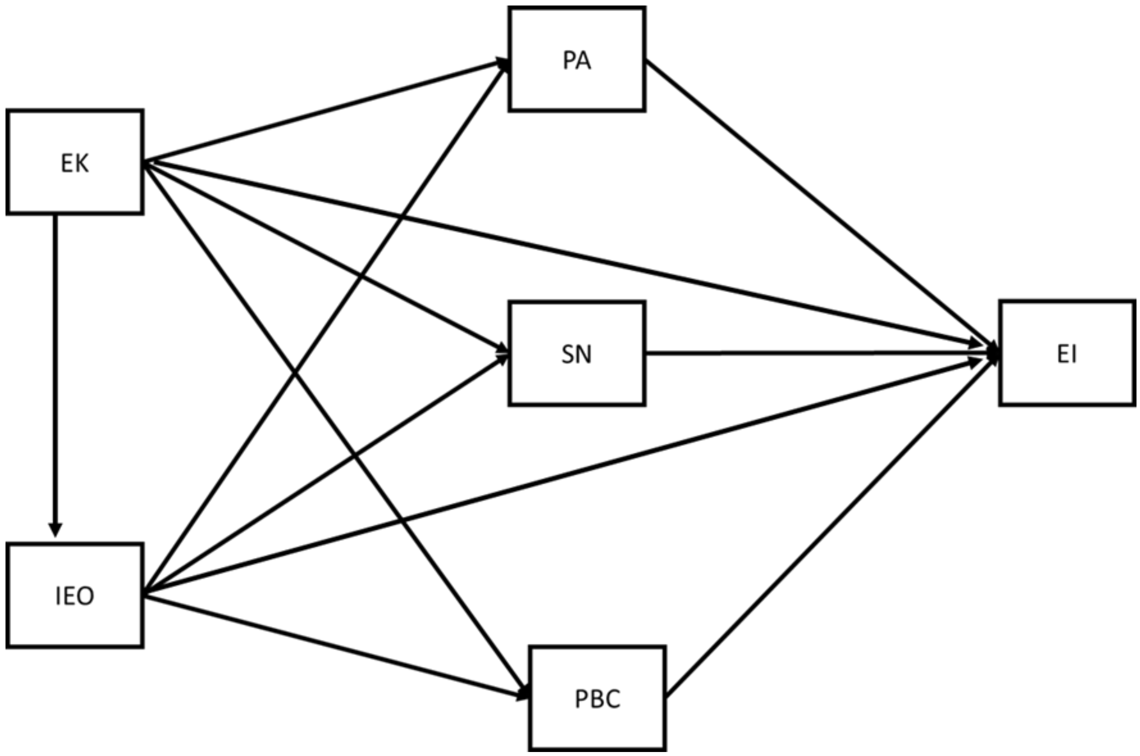

Figure 2: Conceptual Framework

3.2.2 Expert Validation

To ensure content validity, the draft instrument underwent an expert validation process. A panel of five academic experts in entrepreneurship and behavioral sciences evaluated the questionnaire for:

- Clarity of items
- Relevance to constructs
- Cultural appropriateness for Bangladeshi and international students

Experts provided feedback on redundant items, ambiguous wording, and construct alignment. The questionnaire was refined based on their recommendations, improving face and content validity (Lynn, 1986).

3.3 Pilot Testing

Following expert validation, a pilot study was conducted with 100 students drawn from similar demographic characteristics as the target population.

The objectives of the pilot study were to:

- Assess internal consistency reliability (Cronbach's alpha ≥ 0.70 threshold)
- Identify any technical issues in survey administration
- Detect potential biases in item wording

The results of the pilot indicated satisfactory reliability across all constructs (α values ranged between 0.72 and 0.89), confirming readiness for full-scale deployment.

3.4 Sampling Strategy and Participants

3.4.1 Sampling Technique

The study employed a purposive sampling technique to ensure representation from different categories of universities in Bangladesh:

7. International University: Islamic University of Technology (IUT)
8. Private University: Daffodil International University (DIU)
9. Public University: [Mention if included]

Purposive sampling was chosen due to the specific inclusion criteria: participants must be enrolled students who have completed at least two academic semesters, ensuring sufficient exposure to the academic environment and entrepreneurial learning opportunities.

3.4.2 Sample Size Determination

For SEM, an adequate sample size is crucial. According to Hair et al. (2019), a minimum ratio of 10 respondents per estimated parameter is recommended. With an estimated 50 parameters, a minimum of 500 responses was required. Our final sample exceeded this threshold with 600 valid responses, ensuring statistical power.

3.4.3 Sample Composition

Data were collected from two major universities:

Islamic University of Technology (IUT) – An international university under OIC, located in Bangladesh.

Responses: 161 students from 22 OIC member states, with Bangladeshi students forming the largest subgroup.

Daffodil International University (DIU) – A leading private university in Bangladesh.
Responses: 439 students.
Participants included undergraduate students (1st year to 4th year) who had completed at least two semesters, as well as postgraduate students. This distribution allowed for diverse academic exposure and maturity levels.

3.5 Data Collection Procedure

Data collection was conducted via online surveys to maximize reach and convenience. Google Forms was used as the primary platform, and the survey link was distributed through official university channels and student networks.
Participation was voluntary, and informed consent was obtained from all respondents prior to survey completion. No personally identifiable information was collected, ensuring compliance with ethical standards (APA, 2020).

3.6 Data Cleaning and Preprocessing

The raw dataset was exported from Google Forms to Google Colab (Python environment) for preprocessing. Steps included:

1. Handling Missing Data: Cases with more than 20% missing responses were removed. For items with minimal missing values (<5%), mean substitution was applied.
2. Detection of Outliers: Z-score analysis and Mahalanobis distance were used to identify and remove multivariate outliers.
3. Assessment of Normality: Skewness and kurtosis values were computed (threshold ±2 as acceptable).
4. Multicollinearity Check: Variance Inflation Factor (VIF) values were examined (<5 threshold).
5. Data Standardization: For ML modeling, numeric variables were standardized using z-scaling.

After cleaning, 600 complete responses remained for analysis.

3.7 Structural Equation Modeling

3.7.1 Exploratory Factor Analysis (EFA)

To validate the construct structure, EFA was conducted using Principal Axis Factoring with Promax rotation in Python's factor_analyzer library.

- Kaiser-Meyer-Olkin (KMO) Measure: >0.80 (indicating sampling adequacy).
- Bartlett's Test of Sphericity: $p < 0.001$ (confirming factorability).
- Factor Extraction Criteria: Eigenvalues >1 and scree plot inspection.
- Communality Threshold: ≥0.50 for item retention.

Results revealed eight distinct factors corresponding to the integrated theoretical model, explaining 58.8% of total variance.

3.7.2 Confirmatory Factor Analysis (CFA)

After EFA, CFA was performed using Python libraries to validate the measurement model.

Model Fit Indices:

- $\chi^2/df < 3.0$
- CFI, TLI ≥ 0.90
- RMSEA ≤ 0.08
- SRMR ≤ 0.08

Once measurement validity was confirmed, SEM was used to test hypothesized structural relationships among latent variables. Path coefficients, significance levels, and R^2 values were reported.

3.8 Machine Learning Approach

To complement SEM, ML models were applied for predictive analysis.

Algorithms Used:

- Random Forest (RF)
- Gradient Boosting Machines (GBM)
- Support Vector Machine (SVM)

- Artificial Neural Networks (ANN)

3.8.1Model Evaluation Metrics

Performance was assessed using 10-fold cross-validation and metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score
- Area Under the Curve (AUC)

3.8.2 Explainable AI (XAI)

To interpret model predictions, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) were applied. These methods identified the most influential features driving model predictions, enhancing transparency and interpretability.

3.9 Comparison of SEM and ML Results

In the final stage of the analysis, the results obtained from the SEM and ML approaches were systematically compared to highlight their complementary strengths and potential divergences. The comparison focused on three key dimensions:

- **Significant Predictors** – SEM results provided theory-driven evidence of causal relationships through hypothesis testing and path coefficients, while ML identified data-driven predictors of entrepreneurial intention, potentially uncovering additional influential variables not captured by the theoretical model.
- **Predictive Accuracy** – The predictive performance of SEM was assessed through model fit indices and explained variance (e.g., R^2), whereas ML models were evaluated using metrics such as accuracy, precision, recall, and AUC. This allowed for an evaluation of which approach offered superior predictive capability in the context of entrepreneurial intention among students.
- **Interpretability** – SEM offered interpretability through its path diagrams and standardized coefficients, facilitating theoretical understanding of variable relationships. ML results were interpreted through Explainable AI (XAI)

techniques, particularly feature importance and SHAP (SHapley Additive exPlanations) values, which provided insights into how individual predictors contributed to the model's predictions.

By juxtaposing these results, the study was able to determine where theory-driven insights aligned or diverged from data-driven findings, thereby advancing both theoretical understanding and practical prediction of entrepreneurial intention.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Descriptive Analysis

4.1.1 Demographic Information

The demographic characteristics of the respondents provide important contextual insights into the sample under investigation. The age distribution of participants indicates that the majority fall within the younger age brackets, reflecting the nature of the study population as university students. Specifically, 53% of respondents were between the ages of 23 and 28, while 45% were between 17 and 22 years old. Together, these two groups accounted for almost the entire sample, underscoring the predominance of youth in the dataset. Only a very small proportion of respondents were above 29 years, with 0.67% aged 29–34, 0.33% aged 35–40, and 0.5% above 40 years, showing that mature students or late entrants formed a negligible fraction of the overall population. This concentration in the younger age categories is expected given the academic setting of the study.

In terms of gender distribution, the sample displayed a clear dominance of male respondents, who constituted 72.12% of the total participants. Female respondents accounted for 27%, while only 0.86% of participants preferred not to disclose their gender. This pattern of representation highlights a gender imbalance in the study population, which may reflect broader gender dynamics within higher education enrollment in the surveyed institutions.

The academic year breakdown reveals a fairly even spread across different levels of undergraduate study, with a slight concentration in the upper years. The largest group of respondents came from the third year, making up 31.5% of the total sample, closely followed by fourth-year students at 27.6%. First-year students accounted for 27.4%, while second-year students represented the smallest undergraduate group at 12.4%.

Postgraduate students were marginal, comprising only 1.1% of the sample. This distribution suggests that most respondents were relatively advanced in their academic programs, which could influence their perspectives given their greater exposure to university experiences.

With regard to institutional affiliation, most of participants were drawn from a private university setting, specifically Daffodil International University (DIU), which contributed 83% of the sample. The staying 17% of participants were from an international university, Islamic University of Technology (IUT). The predominance of one institution suggests a heavier representation of private university student in the information, though the addition of a global university adds diversity and relative worth to the analysis.

Table 1: Demographic Information

Category		Frequency	Percentage
Age	17 - 22	423	45.532831
	23 - 28	494	53.175457
	29 - 34	6	0.645856
	Above 40	3	0.322928
	35 - 40	3	0.322928
Gender	Male	670	72.12056
	Female	251	27.018299
	Prefer not to say	8	0.861141
Academic Year (AY)	1st Year	255	27.44887
	2nd Year	115	12.378902
	3rd Year	293	31.53929
	4th Year	256	27.556512
	Postgraduate	10	1.076426
University Type	Private University (DIU)	161	17
	International University (IUT)	768	83

Overall, the demographic profile demonstrates that the research study sample is largely made up of young, male undergraduate students, predominantly from a private university, with strong representation from the later phases of scholastic study. These qualities offer an important backdrop for analyzing the findings of the research study, as factors such as age, gender, scholastic direct exposure, and institutional type may all have implications for participants' habits and perceptions.

4.1.2 Preliminary Questions

The initial questions supply a helpful foundation for understanding the entrepreneurial background and direct exposure of the participants, offering insight into their level of prior engagement with entrepreneurship both personally and within their households. For the very first question, "Have you ever began a company?", the responses reveal that a vast majority of individuals (79.67%) have actually not participated in any entrepreneurial activity, while just 20.33% reported having actually begun a business. This suggests that direct entrepreneurial experience amongst the sample is fairly minimal, highlighting a possible space between theoretical understanding and practical application. It likewise implies that entrepreneurial intent among these students may frequently stay at the ideation phase, with fewer individuals taking concrete steps toward implementation.

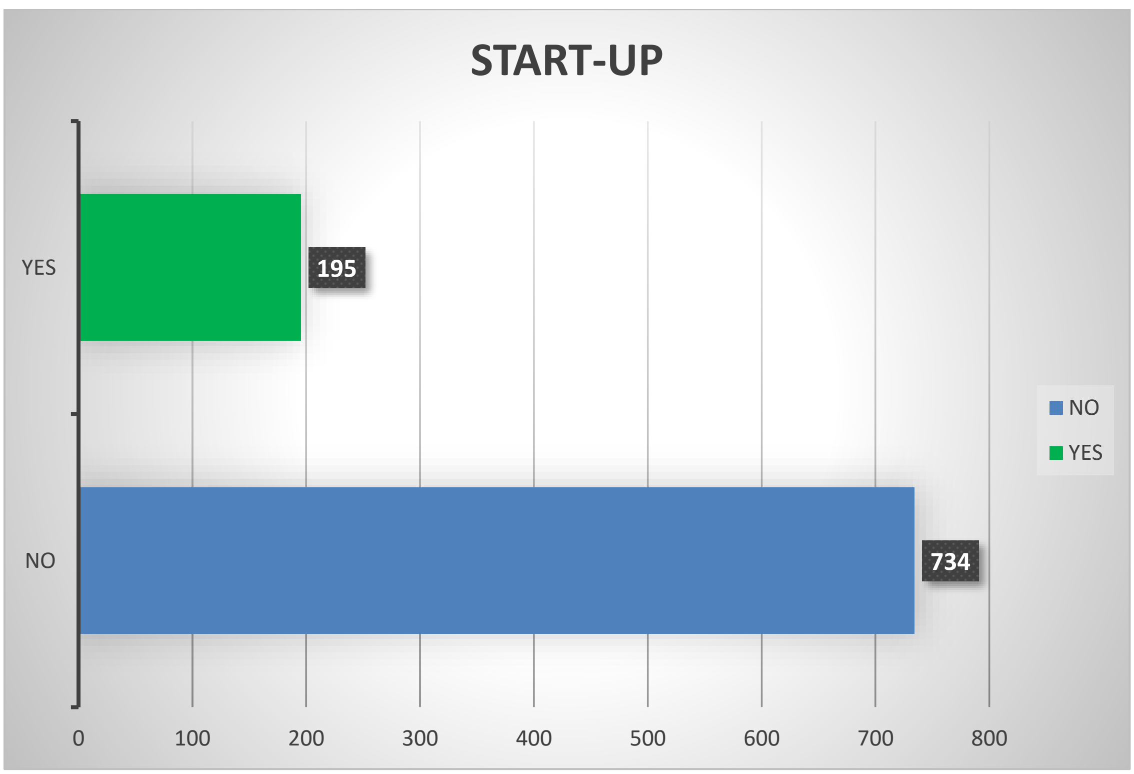

Figure 3: Do you own a business?

The second concern, "Does your family own an organization?", highlights the influence of household background on entrepreneurial orientation. Findings reveal that 66.33% of participants do not come from entrepreneurial families, while 33.67% reported that their households own a service. Due to the fact that earlier research studies indicate that having a family business frequently shapes entrepreneurial objectives by providing role models and access to resources that can inspire students to follow comparable courses, this is noteworthy. The relatively smaller proportion of trainees with entrepreneurial family backgrounds might assist discuss why many have actually not yet taken part in beginning their own endeavors.

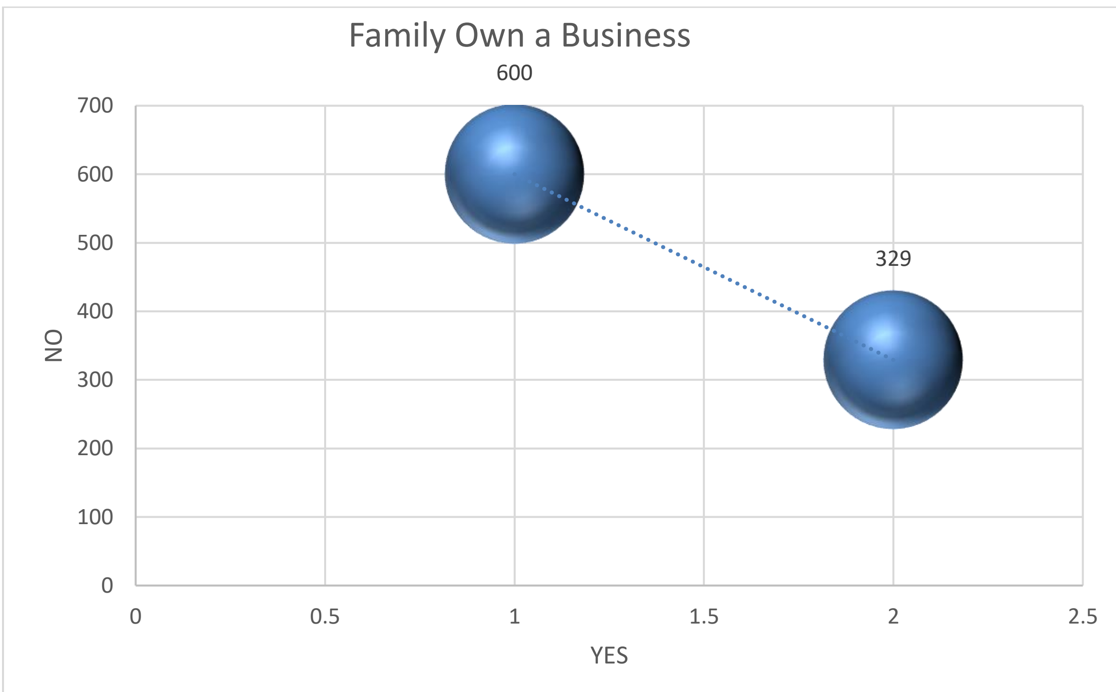

Figure 4: Do your family own a business?

The third concern, "Have you attended any entrepreneurship training?", clarifies the level of official direct exposure to entrepreneurial education. Outcomes reveal that a big majority 86.17% of participants-- have actually never ever gotten involved in such training, while only 13.83% reported having this experience. The restricted direct exposure amongst students underscores the requirement for more appealing and accessible training programs and suggests that numerous students' entrepreneurial intentions may remain underdeveloped due to inadequate institutional or curricular assistance.

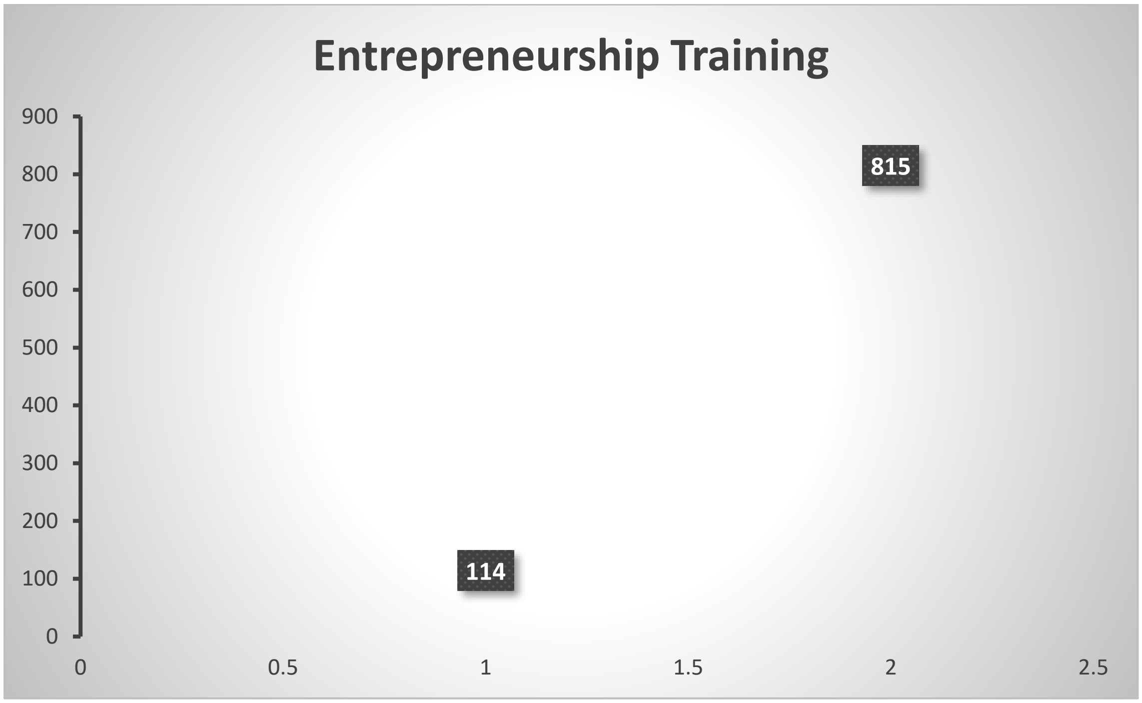

Figure 5: Do you have any entrepreneurship training before?

Together, these preliminary findings highlight the limited direct experience, family influence, and training exposure among respondents, suggesting that while entrepreneurial intention may exist conceptually, structural and experiential barriers may be hindering its translation into practice. This provides a strong justification for further investigation into the psychological and contextual factors that influence entrepreneurial intention in this group.

4.2 Measurement Model Assessment

This study model's entrepreneurial intention (EI) using a hybrid specification that integrates entrepreneurial knowledge (EK) and entrepreneurial orientation (IEO) with the Theory of Planned Behavior (TPB) constructs—attitude (PA), subjective norms (SN), and perceived behavioral control (PBC). All constructs are reflective and measured on seven-point Likert scales.

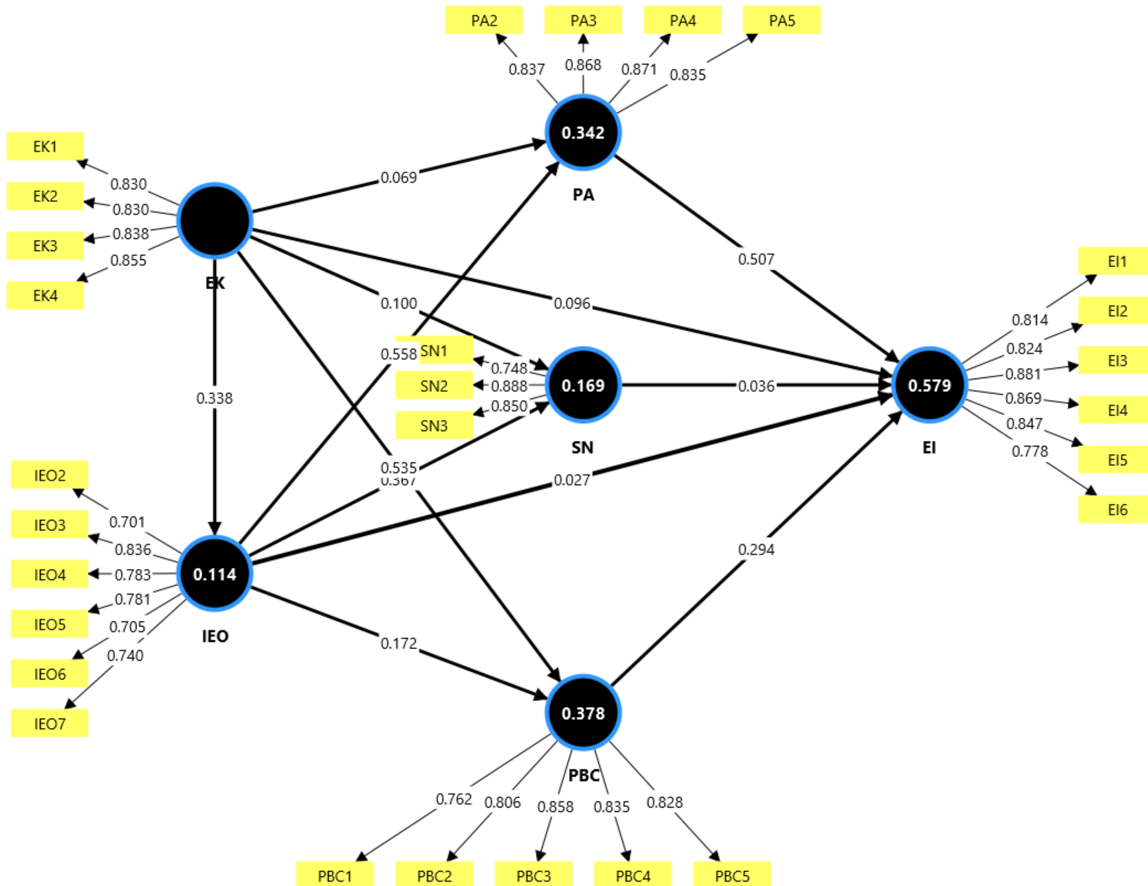

Figure 6: PLS - SEM Algorithm

4.2.1 Indicator reliability

Indicator reliability, when measured by standardized loadings, assesses the amount of variance an individual indicator variable shares with its associated construct (Hair et al., 2020). So as to measure the indicator reliability, just like any other metric, it comes with criteria. The general guideline for measuring standardized loadings should have a value of at least 0.708 [8]. This means that the construct explains at least 49% of the variance of each indicator ($0.7^2 = 0.49$) [9]. However, some researchers suggest a value greater than 0.4 for interpretation purposes. Similarly, others argue that all standardized factor loadings should be at least 0.5. This indicates the construct explains at least 25% of the variance of each indicator ($0.5^2 = 0.25$) [9]. While a standardized loading of 0.708 is ideal for reflective indicators, items may be removed if their loading is statistically significant and falls below other specified thresholds (0.6), especially if this negatively impacts convergent validity. However, removal is not always automatic, and considerations such as the degree of the shortfall, the model type (reflective vs. formative), and theoretical justification play critical roles [10].

All constructs were modeled reflectively and evaluated using SmartPLS 4. Standardized loadings ranged from .622 to .826 for IEO, from .618 to .859 for PA, from .662 to .839 for PBC, from .749 to .888 for SN, from .814 to .881 for EI, and from .829 to .856 for EK. However, following (2021) instructions, items like IEO1, PA1, and PBC6 were removed, which led to a significant improvement in the rest of the items. The Standardized loadings ranged from 0.697 to 0.888 for IEO, from 0.835 to 0.871 for PA, from 0.762 to 0.858 for PBC, from 0.747 to 0.888 for SN, from 0.814 to 0.881 for EI, and from 0.829 to 0.856 for EK (Table X).

2. Measurement Model Evaluation (Final Trimmed Model)

Table 2: : Indicator reliability (standardized loadings)

Items	EI	EK	IEO	PA	PBC	SN
EI1	0.814					
EI2	0.824					
EI3	0.881					
EI4	0.869					
EI5	0.847					
EI6	0.778					
EK1		0.830				
EK2		0.830				
EK3		0.838				
EK4		0.855				
IEO2			0.701			
IEO3			0.836			
IEO4			0.783			
IEO5			0.781			
IEO6			0.705			
IEO7			0.740			
PA2				0.837		
PA3				0.868		
PA4				0.871		
PA5				0.835		
PBC1					0.762	
PBC2					0.806	
PBC3					0.858	
PBC4					0.835	
PBC5					0.828	
SN1						0.748
SN2						0.888
SN3						0.850

All constructs were modeled reflectively and evaluated using SmartPLS 4. Standardized loadings ranged from .622 to .826 for IEO, from .618 to .859 for PA, from .662 to .839 for PBC, from .749 to .888 for SN, from .814 to .881 for EI, and from .829 to .856 for EK. However, following (2021) instructions, items like IEO1, PA1, and PBC6 were removed, which led to a significant improvement in the rest of the items. The

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4.2.2 Construct Reliability and Validity

4.2.2.1 Internal consistency

Table 3 provides an analysis of the internal consistency and convergent validity of several constructs such as Entrepreneurial Intention (EI), Entrepreneurial Knowledge (EK), Idividual Entrepreneurial Orientation (IEO), Personal Attitudes (PA), Perceived Behavioral Control (PBC), and Subjective Norms (SN) based on the provided Cronbach's alpha, rho_A, Composite Reliability (CR, or rho_c), and Average Variance Extracted (AVE) values. These metrics are fundamental for assessing the quality of reflective measurement models within Structural Equation Modeling (SEM) [8]. It is important to note that a comprehensive assessment of measurement model quality also involves evaluating overall model fit indices and accounting for sampling errors through bootstrapped confidence intervals (CIs), especially 90% percentile CIs, for statistical tests of these criteria.

Table 3: Internal consistency and convergent validity

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
EI	0.914	0.915	0.933	0.699
EK	0.860	0.864	0.904	0.703
IEO	0.852	0.856	0.890	0.576
PA	0.875	0.875	0.914	0.727
PBC	0.876	0.880	0.910	0.670
SN	0.772	0.784	0.869	0.690

Internal consistency evaluates the extent to which items within a scale are intercorrelated and measure the same underlying construct [9].Cronbach's alpha is a widely reported measure of internal consistency reliability. A value greater than 0.70 is generally considered acceptable, but a threshold of 0.80 or higher is often recommended for most studies, as 0.70 indicates only modest reliability .However, values 0.95 or higher can indicate redundancy, where items may be measuring the exact same concept, thus lacking diversity for construct validity. Cronbach's alpha is not SEM-based and typically underestimates the reliability of a latent construct when factor loadings are unequal, as it assumes tau-equivalence (equal factor loadings) [9]. It also ignores sampling errors, which can limit the generalizability of conclusions. From our Analysis EI shows an excellent alpha value of 0.914, well above the 0.80 recommended threshold. It approaches 0.95, which could indicate a minor concern for potential redundancy, though it does not strictly exceed the 0.95 mark. Similarly EK 0.860, IEO 0.852, PA 0.875, and PBC 0.876 are excellent, significantly above the 0.80 threshold showing strong internal consistency. Although SN 0.772 shows value that is acceptable, surpassing the 0.70 threshold. However, it falls below the ideal 0.80 benchmark, suggesting modest rather than strong reliability.

rho_A is another measure of internal consistency reliability, often alongside Cronbach's alpha and Composite Reliability (CR) (Fawaid et al., 2022). In practice, it is often interpreted similarly to other reliability measures. EI (rho_A = 0.915) value is very high, consistent with the excellent Cronbach's alpha and CR for EI. EK (rho_A = 0.865),IEO (rho_A = 0.855), PA (rho_A = 0.875), and PBC (rho_A = 0.880) values are strong, aligning with the other reliability measures. Although SN (rho_A = 0.784) value is acceptable, similar to its Cronbach's alpha and showing a good level of internal consistency.

Composite Reliability (CR or rho_c) is considered a more appropriate SEM-based reliability measure than Cronbach's alpha, as it is a weighted measure that accounts for unequal factor loadings (congeneric model) [10]. The recommended threshold is 0.70 or higher, indicating good reliability. Ideally, values should not be significantly lower than 0.80. For newly developed measures, a lower threshold of 0.60 may sometimes be accepted [9]. Reporting CR is crucial for latent constructs used in analyses. In our analysis, EI shows CR = 0.933, this value is excellent, significantly above the 0.80 ideal threshold. It suggests strong reliability for the construct. Likewise EK (CR = 0.904), IEO (CR = 0.891), PA (CR = 0.914), PBC (CR = 0.910), and SN (CR = 0.869) values are excellent,well above the recommended 0.80, and demonstrating high reliability.

Convergent validity assesses the extent to which multiple indicators of a construct agree with each other and converge on the theoretical concept they are intended to measure (Hair et al., 2020). in SEM, Average Variance Extracted (AVE) is used in assing Convergent validity. AVE quantifies the average amount of variance that a latent construct explains in its indicators, relative to the total variance of those indicators [10]. The most common criterion for acceptable convergent validity is an AVE value of 0.50 or higher (50%), which suggests that the latent construct explains at least half of the variance in its associated indicators [8]. AVE is a rule-of-thumb criterion that often ignores sampling errors [9]. From our analysis EI (AVE = 0.699), EK (AVE = 0.703), IEO (AVE = 0.576), PA (AVE = 0.727),PBC (AVE = 0.670), SN (AVE = 0.690) are significant, excellent, well above the 0.50 threshold, and indicating strong convergent validity.

Based on the provided point estimates, all constructs (EI, EK, IEO, PA, PBC, and SN) demonstrate strong internal consistency and reliability, as indicated by both Cronbach's alpha and Composite Reliability values well above commonly accepted thresholds of 0.70 and generally above the ideal 0.80 benchmark. Furthermore, all constructs exhibit strong convergent validity, with Average Variance Extracted values consistently above the 0.50 criterion. In particular EI, EK, IEO, PA, PBC show consistently excellent reliability and convergent validity across all reported metrics. For EI, PA, and PBC, the high alpha and CR values (above 0.90) are excellent but should be mindful of the "0.95 or higher" rule for potential item redundancy in future, more detailed analyses. SN shows acceptable Cronbach's alpha (0.772) and excellent Composite Reliability (0.869) and AVE (0.690), indicating that while its alpha is modest, its SEM-based reliability and convergent validity are strong. These findings suggest that the measurement models for all listed constructs are robust in terms of internal consistency and convergent validity

4.2.2.1 Discriminant Validity

This report presents an in-depth analysis of the discriminant validity of six constructs and the assessment is based on Heterotrait-Monotrait (HTMT) ratio matrix and the Fornell-Larcker criterion matrix, which are crucial for evaluating the quality of reflective measurement models within Structural Equation Modeling (SEM) contexts, particularly PLS-SEM as inferred from our previous discussion on internal consistency and convergent validity metrics. Before going deeper into the specific results, it is important to reiterate that a comprehensive assessment of measurement model quality also requires establishing overall model fit and ensuring that no indicator cross-loads on other constructs, meaning each indicator should be related directly to only one construct [9]. Discriminant validity is a critical aspect of construct validity, assessing the extent to which a construct is truly distinct from other constructs in a model [10]. It measures the uniqueness between constructs, ensuring that a construct is measuring attributes different from other constructs (Shwedeh et al., 2023). If constructs are not sufficiently distinct, their relationships cannot be meaningfully interpreted. Two primary criteria are commonly used to assess discriminant validity: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio

Table 4: HTMT discriminant validity matrix

Constructs	EI	EK	IEO	PA	PBC	SN
EI						
EK	**0.469**					
IEO	0.530	**0.386**				
PA	0.758	0.293	**0.670**			
PBC	0.636	0.679	0.402	**0.442**		
SN	0.479	0.272	0.488	0.538	**0.468**	

Heterotrait-Monotrait (HTMT) Ratio of Correlations is a recently recommended criterion for assessing discriminant validity, particularly in variance-based SEM methods like PLS-SEM [10]. It is calculated as the ratio of the average heterotrait-heteromethod inter-item correlations to the geometric mean of the monotrait-heteromethod inter-item correlations [9]. A commonly suggested threshold for HTMT is 0.85, where values below this threshold indicate discriminant validity. Some researchers also suggest a more lenient threshold of 0.90 [11]. Values above these thresholds suggest that constructs are not sufficiently distinct.EI and EK: HTMT = 0.469, which is < 0.85. (Pass), EI and IEO: HTMT = 0.530, which is < 0.85. (Pass), EI and PA: HTMT = 0.758, which is < 0.85. (Pass), EI and PBC: HTMT = 0.636, which is < 0.85. (Pass), EI and SN: HTMT = 0.479, which is < 0.85. (Pass), EK and IEO: HTMT = 0.386, which is < 0.85. (Pass), EK and PA: HTMT = 0.293, which is < 0.85. (Pass), EK and PBC: HTMT = 0.679, which is < 0.85. (Pass), EK and SN: HTMT = 0.272, which is < 0.85. (Pass), IEO and PA: HTMT = 0.670, which is < 0.85. (Pass), IEO and PBC: HTMT = 0.402, which is < 0.85. (Pass), IEO and SN: HTMT = 0.488, which is < 0.85. (Pass), PA and PBC: HTMT = 0.442, which is < 0.85. (Pass), PA and SN: HTMT = 0.538, which is < 0.85. (Pass), PBC and SN: HTMT = 0.468, which is < 0.85. (Pass). All pairwise HTMT values between the constructs are below the 0.85 threshold. This indicates that all constructs demonstrate strong discriminant validity based on the HTMT criterion

Table 5: Fornell–Larcker criterion (√AVE on diagonal).

Constructs	EI	EK	IEO	PA	PBC	SN
EI	**0.836**					
EK	0.419	**0.838**				
IEO	0.473	0.338	**0.759**			
PA	0.678	0.258	0.581	**0.853**		
PBC	0.571	0.593	0.353	0.388	**0.818**	
SN	0.405	0.224	0.400	0.443	0.379	**0.831**

Fornell-Larcker Criterion is used to assess discriminant validity which suggests that discriminant validity is established when the Average Variance Extracted (AVE) for each construct is greater than the squared correlation (shared variance) between that construct and all other constructs in the model [12]. In practice, this means that the square root of the AVE often presented on the diagonal of a correlation matrix, for each construct should be greater than its correlations with all other constructs in its corresponding row and column. The AVE itself should ideally be 0.50 or higher, indicating that the latent construct explains at least 50% of the variance in its associated indicators (Cheung et al., 2024). According to our results, Entrepreneurial Intention (EI) (0.836),Entrepreneurial Knowledge (EK) (0.838), Individual Entrepreneurial Orientation (IEO) (0.759),Personal Attitudes (PA) (0.853), Perceived Behavioral Control (PBC) (0.818), and Subjective Norms (SN) (0.831) values are higher than all their respective correlations with other constructs. (0.419 with EK, 0.471 with IEO, 0.678 with PA, 0.571 with PBC, and 0.405 with SN). This concludes that all six constructs (EI, EK, IEO, PA, PBC, SN) satisfy the Fornell-Larcker criterion, as the square root of their respective AVEs is greater than their correlations with all other constructs in the model. This indicates good discriminant validity based on this criterion

Both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio provide consistent and strong evidence for the discriminant validity of the six constructs: Entrepreneurial Intention (EI), Entrepreneurial Knowledge (EK), International Entrepreneurial Orientation (IEO), Personal Attitudes (PA), Perceived Behavioral Control (PBC), and Subjective Norms (SN).The Fornell-Larcker criterion demonstrates that each construct shares more variance with its own indicators than with any other construct in the model. The HTMT ratios further confirm that all inter-construct correlations are sufficiently low, falling well below the commonly accepted thresholds of 0.85 or 0.90. These findings, in conjunction with the previously established strong internal consistency and convergent validity (as discussed in our prior conversation), suggest that the measurement models for all constructs are robust and distinct from each other. This robust measurement quality allows for greater confidence in interpreting the structural relationships among these constructs in subsequent hypothesis testing. However, for future research, it would be beneficial to include statistical tests with bootstrapped confidence intervals for these measures to account for sampling error and provide an even more rigorous assessment of discriminant validity [9]

4.2.3 Structural Model Evaluation

Quality criteria that is R-square, R-square Adjust, and F-square, drawing on the sources, these metrics are crucial for evaluating the quality of a structural equation model, particularly in Partial Least Squares Structural Equation Modeling (PLS-SEM), which focuses on prediction and explanation of variance [10].

4.2.3.1 R-square (R^2) and Adjusted R-square (R^2 - adj)

The R-square (R^2), also known as the coefficient of determination, is a key metric for assessing the model's predictive accuracy and explanatory power [6]. In PLS-SEM, the objective is to maximize the R^2 values of the endogenous (target) constructs, reflecting its in-sample prediction objective. The R^2 value indicates the proportion of the variance in a dependent variable that is explained by its predictor variables. The "Adjusted R-square" systematically adjusts the R^2 value downward, taking into account the sample size and the number of predictive constructs in the model, and is particularly useful when many non-significant predictors are included (Amofah & Saladrigues, 2022). For interpreting the size of R^2 values, common guidelines suggest:

- Substantial: R^2 values above 0.67.
- Moderate: R^2 values above 0.33.
- Weak: R^2 values above 0.19.

Table 6: Explanatory Power - R^2 and R^2-adjusted

Constructs	R-square	R-square adjusted
EI	0.579	0.577
IEO	0.114	0.113
PA	0.342	0.340
PBC	0.378	0.377
SN	0.169	0.167

R-square

EI (Endogenous Variable) With an R^2 of 0.579, the model demonstrates a moderate to substantial explanatory power for EI. This means approximately 57.9% of the variance in EI is explained by its predictors. The high T statistic (21.144) and P value of 0.000 indicate that this R^2 is highly significant. IEO, the R^2 value of 0.114 suggests a weak explanatory power for IEO. This indicates that only 11.4% of the variance in IEO is explained. Despite the low R^2, the T statistic (5.412) and P value (0.000) show that this explained variance is statistically significant. PA (Personal Attitudes) an R^2 of 0.342 indicates a moderate explanatory power for PA. About 34.2% of the variance in PA is explained. The T statistic (10.994) and P value (0.000) confirms its statistical significance. PBC (Perceived Behavioral Control) With an R^2 of 0.378, the model shows moderate explanatory power for PBC, leaning towards substantial. Approximately 37.8% of the variance in PBC is explained, and this is statistically significant (T=12.084, P=0.000). SN (Subjective Norms): The R^2 of 0.169 indicates weak explanatory power for SN. Only 16.9% of the variance in SN is explained, yet this is statistically significant (T=6.876, P=0.000).

R-square adjust

Table 6 shows R-square Adjusted. The adjusted R-square values are consistently slightly lower than the unadjusted R-square values, which is expected as they account for model complexity and sample size. All adjusted R-square values remain very close to their unadjusted counterparts, suggesting that the number of predictors in the model is not excessively large relative to the sample size, or that the included predictors are generally contributing meaningfully to the explanation of variance. The statistical significance (T-statistics and P-values) for the adjusted R-square values are also consistent with the unadjusted R-square, reinforcing the reliability of these findings.

4.2.3.2 The F-square (f^2)

The F-square (f^2) statistic measures the effect size of each independent construct on a dependent construct in the model. It provides an estimate of the predictive ability of each independent construct. To calculate this value, each predictor construct is systematically removed from the model, and a new R^2 is calculated without that predictor. The difference in the two R^2 values indicates whether the omitted construct is a meaningful predictor of the dependent construct.

Cohen (1988) provides guidelines for interpreting f^2 values:

- Small effect: Values between 0.02 and 0.15.
- Medium effect: Values between 0.15 and 0.35.
- Large effect: Values 0.35 and above.
- No effect: Values less than 0.02.

Table 7: F-square (f^2)

Effects	f-square
EK -> EI	0.014
EK -> IEO	0.129
EK -> PA	0.006
EK -> PBC	0.408
EK -> SN	0.011
IEO -> EI	0.001
IEO -> PA	0.419
IEO -> PBC	0.042
IEO -> SN	0.143
PA -> EI	0.360
PBC -> EI	0.115
SN -> EI	0.002

Table 8 Shares F-square values for various paths. EK -> EI: $F^2 = 0.014$. This indicates no effect or a very small effect of EK on EI, as it is below the 0.02 threshold for a small effect. The P value of 0.088 (T=1.355) indicates it is not statistically significant at the customary 5% level (T-statistic > 1.96 for 5% significance). EK -> IEO, $F^2 = 0.129$ is considered a small effect of EK on IEO. It is statistically significant (T=4.740,

P=0.000).EK -> PA, F^2 = 0.006 has a no effect of EK on PA. It is not statistically significant (T=1.066, P=0.143).EK -> PBC, F^2 = 0.408 represents a large effect of EK on PBC. It is highly statistically significant (T=6.199, P=0.000). EK -> SN, F^2 = 0.011 indicates no effect of EK on SN. It is not statistically significant (T=1.343, P=0.090), IEO -> EI: F^2 = 0.001 shows no effect of IEO on EI. It is not statistically significant (T=0.342, P=0.366). IEO -> PA, F^2 = 0.419 is a large effect of IEO on PA. It is highly statistically significant (T=6.511, P=0.000). IEO -> PBC, F^2 = 0.042 is a small effect of IEO on PBC. It is statistically significant (T=2.700, P=0.003). IEO -> SN, F^2 = 0.143 is a small effect of IEO on SN. It is statistically significant (T=4.671, P=0.000). PA -> EI, F^2 = 0.360 indicates a large effect of PA on EI. It is highly statistically significant (T=5.782, P=0.000).PBC -> EI, F^2 = 0.115 is a small effect of PBC on EI. It is statistically significant (T=4.074, P=0.000). SN -> EI, F^2 = 0.002 shows no effect of SN on EI. It is not statistically significant (T=0.531, P=0.298).

Based on the R-square and F-square results, the model's quality can be summarized as follows: Explanatory Power (R^2) shows that the model demonstrates strong explanatory power for EI (0.579) and moderate explanatory power for PA (0.342) and PBC (0.378). However, the explanatory power for IEO (0.114) and SN (0.169) is weak. All reported R^2 values are statistically significant, even the weak ones, indicating that the observed variances are not due to chance. Predictive Relevance (F^2),s reveal several important relationships such as large effects are observed from EK -> PBC (0.408), IEO -> PA (0.419), and PA -> EI (0.360). These paths are significant and contribute substantially to the R^2 of their respective endogenous constructs. Similarly indicates Small effects are present for EK -> IEO (0.129), IEO -> PBC (0.042), IEO -> SN (0.143), and PBC -> EI (0.115). These contributions are modest but statistically significant. No significant effects are found for EK -> EI (0.014), EK -> PA (0.006), EK -> SN (0.011), IEO -> EI (0.001), and SN -> EI (0.002). This suggests that these specific direct relationships might not be critical drivers in the model, or their effects are negligible.

4.2.4 Predictive Relevance (Q^2predict) and Out-of-Sample Prediction (PLSpredict)

In Partial Least Squares Structural Equation Modeling (PLS-SEM), a core objective is prediction and explanation of variance[10]. While R^2 values measure in-sample prediction, and the Q^2 (blindfolding) value combines aspects of out-of-sample prediction and in-sample explanatory power, PLSpredict offers a robust method to assess out-of-sample prediction [10]. Out-of-sample prediction is crucial because in-sample prediction (using the same sample to estimate and predict) can lead to overfitting, overstating the model's predictive ability for new observations. PLSpredict uses k-fold cross-validation, where the total sample is randomly split into subgroups (folds). The model is estimated on a training sample (k-1 subgroups) and then used to predict a separate holdout sample (the remaining subgroup). This process is repeated, ensuring each case is predicted by a model estimated without that case. For assessing predictive power using PLSpredict, researchers evaluate several prediction statistics that quantify prediction error [8].

4.2.4.1 Q^2predict Cross-Validated Predictive Relevance

The Q^2predict statistic is the first metric to evaluate in PLSpredict results. It helps to verify that the model's predictions outperform a naive benchmark, which is defined as the indicator means from the analysis sample. A Q^2predict value greater than 0 for a specific endogenous construct indicates predictive relevance for that construct[13].

Table 8: Q^2predict Cross-Validated Predictive Relevance

Constructs	Q^2predict	RMSE	MAE
EI	0.173	0.911	0.737
IEO	0.112	0.945	0.731
PA	0.063	0.970	0.788
PBC	0.350	0.808	0.624
SN	0.047	0.978	0.790

EI, Q^2predict value of 0.173 is greater than 0, indicating that the model has predictive relevance for Entrepreneurial Intention (EI). IEO Q^2predict value of 0.112 is greater than 0, suggesting predictive relevance for IEO. PA With a Q^2predict of 0.063, the model shows predictive relevance for Personal Attitudes (PA). PBC Q^2predict value of 0.350 is substantially greater than 0, demonstrating strong predictive relevance for Perceived Behavioral Control (PBC). This is the highest Q^2predict value among your constructs. SN (0.047) Q^2predict value of 0.047, while low, is greater than 0, indicating predictive relevance for Subjective Norms (SN). All endogenous constructs in your model show positive Q^2predict values, confirming that the model's predictions for these constructs are better than a naive benchmark.

4.2.4.2 Out-of-Sample Prediction (PLS vs. Linear Benchmark)

This table compares the prediction errors of your PLS-SEM model against a linear regression model (LM) benchmark. The LM benchmark generates predictions for the manifest variables (indicators) of the endogenous constructs from all indicators of the exogenous latent variables in the PLS path model, but it does not include the specified model structure. The main prediction error statistics used for this comparison are the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). RMSE is generally preferred because it gives greater weight to larger errors, which is often desirable in business research. MAE is used if the prediction error distribution is highly non-symmetric. In your tables, "PLS loss" and "LM loss" likely refer to the RMSE or MAE values for your PLS model and the Linear Benchmark model, respectively. The average loss difference, t-value, and p-value assess if the difference in predictive error between the two models is statistically significant.

Here are the guidelines for interpreting the comparison of RMSE (or MAE) values with the LM benchmark:

- Lacks predictive power: PLS model yields higher prediction errors for all dependent variable indicators compared to the LM benchmark.
- Low predictive power: PLS model yields higher prediction errors for the majority of dependent construct indicators compared to the LM benchmark.
- Medium predictive power: PLS model yields higher prediction errors for a minority (or the same number) of indicators compared to the LM benchmark.

- High predictive power: PLS model yields none of the indicators with higher prediction errors compared to the LM benchmark.

Let's analyze your "Out-of-sample prediction" table:

Table 9: Out-of-Sample Prediction

Constructs	PLS loss	LM loss	Average loss difference	t-value	p-value
EI	3.039	3.041	-0.002	0.184	0.854
IEO	2.706	2.685	0.022	1.492	0.136
PA	3.026	3.017	0.009	0.570	0.569
PBC	2.465	2.459	0.006	0.469	0.639
SN	3.280	3.273	0.006	0.376	0.707
Overall	2.864	2.856	0.008	0.912	0.362

EI has PLS loss (3.039) is slightly lower than LM loss (3.041), Average loss difference: -0.002 and a T-value (0.184) and P-value (0.854) indicate the difference is not statistically significant.However The PLS model performs slightly better than the LM benchmark for EI, though not significantly. IEO, PLS loss (2.706) is slightly higher than LM loss (2.685), Average loss difference: 0.022, and T-value (1.492) and P-value (0.136) indicate the difference is not statistically significant. The PLS model performs slightly worse than the LM benchmark for IEO, but not significantly. PA PLS loss (3.026) is slightly higher than LM loss (3.017). Average loss difference: 0.009. T-value (0.570) and P-value (0.569) indicate the difference is not statistically significant. Interpretation: The PLS model performs slightly worse than the LM benchmark for PA, but not significantly. PBC: PLS loss (2.465) is slightly higher than LM loss (2.459). Average loss difference: 0.006. T-value (0.469) and P-value (0.639) indicate the difference is not statistically significant. Interpretation: The PLS model performs slightly worse than the LM benchmark for PBC, but not significantly. SN: PLS loss (3.280) is slightly higher than LM loss (3.273). Average loss difference: 0.006. T-value (0.376) and P-value (0.707) indicate the difference is not statistically significant. Interpretation: The PLS model performs slightly worse than the LM benchmark for SN, but not significantly.

Overall, PLS loss (2.864) is slightly higher than LM loss (2.856). Average loss difference: 0.008. T-value (0.912) and P-value (0.362) indicate the difference is not statistically significant. Overall Predictive Power Assessment, For all constructs (EI, IEO, PA, PBC, SN), the PLS model's prediction errors (PLS loss) are either slightly lower (for EI) or slightly higher (for IEO, PA, PBC, SN) than the naive Linear Benchmark (LM loss). Crucially, the differences in prediction errors are not statistically significant for any individual construct or for the overall model, as indicated by the high p-values (all > 0.05). Applying the guidelines For EI, the PLS model has a lower prediction error than the LM benchmark (though not significantly). For IEO, PA, PBC, and SN, the PLS model has higher prediction errors than the LM benchmark (though not significantly).

Since none of the indicators in the PLS-SEM analysis show significantly higher RMSE (or MAE) values compared to the naive LM benchmark, the model demonstrates medium predictive power for the majority of the constructs. Specifically, while the PLS model does not overwhelmingly outperform the simple linear regressions for most constructs, it also does not perform significantly worse. The overall model's predictive performance is not significantly different from the simple benchmark, suggesting that while the theoretical model might provide additional insights into the relationships between constructs, its predictive accuracy for unseen data, as measured by PLSpredict against a basic linear benchmark, is moderate at best. The non-significant differences imply that the structural complexity of your PLS model, while theoretically driven, does not provide a substantial predictive advantage over a simpler linear regression model for these specific dependent variables in an out-of-sample context.

4.2.5 Path Coefficients in PLS-SEM

Path coefficients represent the strengths and directions of the hypothesized relationships between constructs in a structural model. In the context of PLS-SEM, these coefficients are estimated with the objective of maximizing the R^2 values (explained variance) of the endogenous (dependent) constructs. Single-headed arrows in a path model depict these directional relationships, which are considered predictive and, with strong theoretical support, can be interpreted as causal. Path coefficients are standardized values, typically ranging from +1 to -1. Values closer to the absolute value of 1 indicate stronger predictive relationships, while values closer to 0 indicate weaker ones. The table you provided shows bootstrapped path coefficients, which is a common and robust method for assessing the statistical significance of these relationships in PLS-SEM [8].

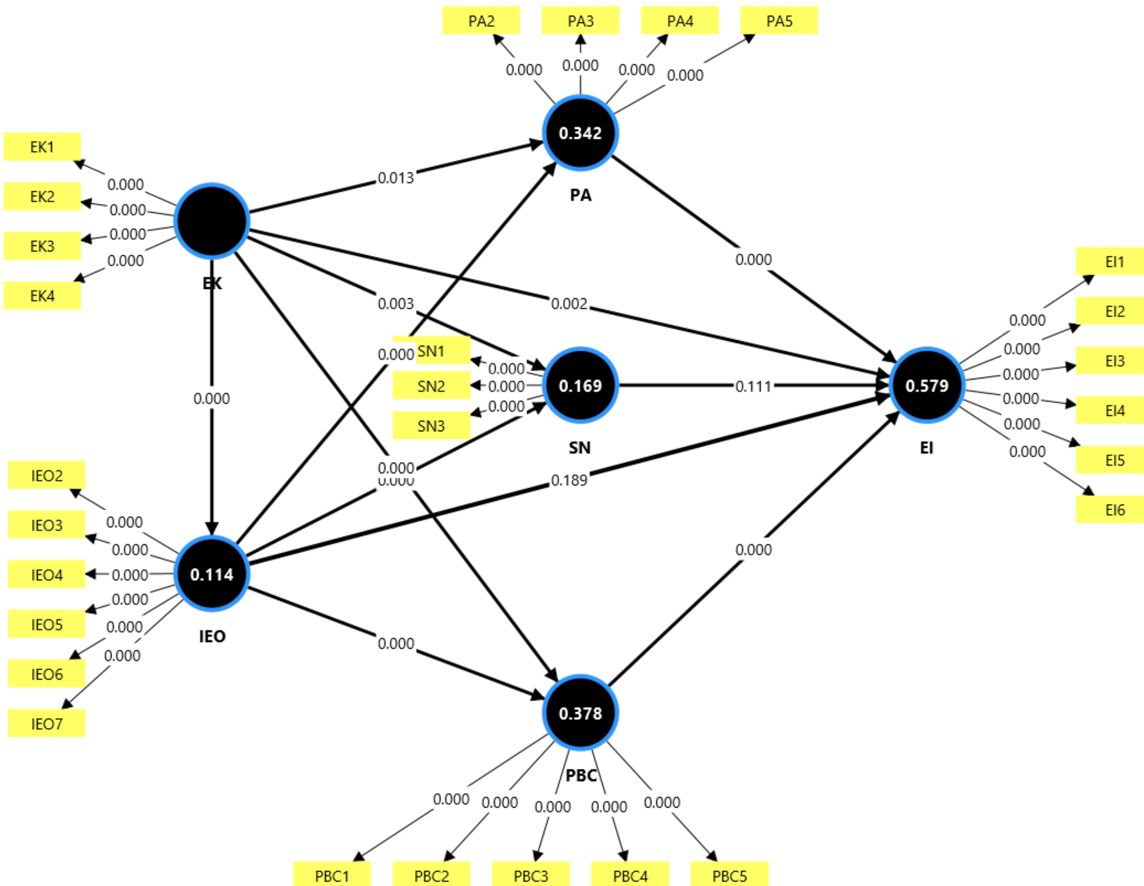

Figure 7: PLS - SEM Bootstrapping

Bootstrapping is a non-parametric resampling technique used in PLS-SEM to generate standard errors and T-statistics for path coefficients, without making assumptions about the data distribution. The table specifies that 10,000 subsamples were used, and BCa (Bias-Corrected and Accelerated) 95% confidence intervals were applied. The T-statistics are calculated by dividing the original sample coefficient by its standard deviation. For a two-tailed test, a path coefficient is generally considered statistically significant at the 5% level if its T-statistic is larger than 1.96 and its P-value is less than 0.05 [10].

Table 10: Bootstrapped path coefficients

Constructs	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
EK -> EI	0.096	0.096	0.034	2.825	0.002
EK -> IEO	0.338	0.339	0.031	10.856	0.000
EK -> PA	0.069	0.069	0.031	2.229	0.013
EK -> PBC	0.535	0.536	0.031	17.150	0.000
EK -> SN	0.100	0.100	0.036	2.792	0.003
IEO -> EI	0.027	0.027	0.031	0.880	0.189
IEO -> PA	0.558	0.558	0.030	18.718	0.000
IEO -> PBC	0.172	0.173	0.031	5.594	0.000
IEO -> SN	0.367	0.367	0.034	10.649	0.000
PA -> EI	0.507	0.507	0.032	15.970	0.000
PBC -> EI	0.294	0.294	0.034	8.702	0.000
SN -> EI	0.036	0.036	0.029	1.222	0.111

IEO -> PA (0.558) is the strongest positive effect observed, indicating that IEO is a very strong predictor of PA. EK -> PBC (0.535) also shows a strong positive effect, suggesting that EK significantly influences PBC. PA -> EI (0.507) demonstrates a strong positive effect, indicating that Personal Attitudes are a strong predictor of Entrepreneurial Intention. EK -> IEO (0.338), IEO -> SN (0.367), PBC -> EI (0.294) demonstrate Moderate Relationships EK -> EI (0.096), EK -> PA (0.069), EK -> SN (0.100), IEO -> PBC (0.172) show Weak but Significant Relationships. IEO -> EI (0.027) and SN -> EI (0.036) Non-Significant Relationships. These non-significant paths suggest that, despite the presence of other significant relationships in your model, IEO and SN do not directly or significantly influence EI. This could have implications for the theoretical framework, possibly suggesting that their influence on EI is entirely mediated by other constructs, or that these specific direct relationships are not present in your data. It's important to remember that PLS-SEM is a "causal–predictive" approach that focuses on explaining the variance in dependent variables [10]. The analysis of these path coefficients, along with the R^2 and F^2 values discussed previously, contributes to a comprehensive understanding of the model's explanatory and predictive power.

4.2.6 Mediation Analysis

4.2.6.1 Total Indirect Effects

Bootstrapped mediation estimates indicate that entrepreneurial knowledge (EK) and individual entrepreneurial orientation (IEO) operate chiefly through the belief structures of the TPB rather than exerting direct effects on intention. The total indirect effect from EK to entrepreneurial intention (EI) is $\beta = 0.322$ ($t = 10.218$, $p < .001$), which means that after accounting for all mediating pathways, a one–standard deviation increase in EK translates into roughly one-third of a standard deviation increase in EI. In this specification there is no direct EK→EI path; the influence of knowledge is therefore fully transmitted through downstream constructs. The decomposition of EK's total mediation shows three statistically strong channels: EK increases attitude toward entrepreneurship (PA) with an indirect effect of $\beta = 0.188$ ($t = 9.395$, $p < .001$), raises perceived behavioral control (PBC) with $\beta = 0.058$ ($t = 4.970$, $p < .001$), and elevates subjective norms (SN) with $\beta = 0.124$ ($t = 7.259$, $p < .001$). Given that the structural model established PA→EI ($\beta = 0.524$, $p < .001$) and PBC→EI ($\beta = 0.353$, $p < .001$) as the dominant proximal drivers of intention—while SN→EI was trivial and non-significant ($\beta = 0.039$, $p = .175$)—the practical contribution of EK to EI flows mainly through the PA and PBC branches. The path through SN, despite being statistically different from zero in the mediation decomposition, contributes little to final intention because the final leg from SN to EI carries negligible weight in this cohort.

Table 11: Total indirect effects

Effects	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
EK -> EI	0.322	0.324	0.032	10.218	0.000
EK -> PA	0.188	0.189	0.020	9.395	0.000
EK -> PBC	0.058	0.058	0.012	4.970	0.000
EK -> SN	0.124	0.125	0.017	7.259	0.000
IEO -> EI	0.347	0.347	0.026	13.360	0.000

IEO displays a similar mediated influence on intention. Its total indirect effect on EI is $\beta = 0.347$ ($t = 13.360$, $p < .001$), indicating that the orientation profile of students translates into higher intention only insofar as it reshapes their beliefs about entrepreneurship. The strongest conduit is the route from IEO to PA ($\beta = 0.557$, $p < .001$), which then feeds into EI through the substantial PA→EI link. Smaller but statistically reliable channels connect IEO to PBC ($\beta = 0.171$, $p < .001$) and to SN ($\beta = 0.366$, $p < .001$); however, as with the EK case, the practical leverage of the SN branch is muted by the weak SN→EI association. Altogether, the mediation results sharpen the explanatory narrative of the model: knowledge and orientation matter because they cultivate favorable attitudes and a sense of control, and those two beliefs, not normative pressure, are what ultimately move entrepreneurial intention among CSE students in Bangladesh.

4.2.6.2 Specific Indirect Effects

The decomposition of specific indirect effects clarifies precisely how entrepreneurial knowledge (EK) and individual entrepreneurial orientation (IEO) transmit their influence to entrepreneurial intention (EI) through the TPB belief set. All coefficients are standardized and bootstrapped.

Table 12: Specific indirect effects

Effects	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
EK -> IEO -> PA	0.188	0.189	0.020	9.395	0.000
EK -> IEO -> PBC	0.058	0.058	0.012	4.970	0.000
EK -> IEO -> SN	0.124	0.125	0.017	7.259	0.000
EK -> IEO -> PBC -> EI	0.017	0.017	0.004	4.322	0.000
EK -> IEO -> PA -> EI	0.096	0.096	0.012	8.130	0.000
EK -> IEO -> SN -> EI	0.004	0.005	0.004	1.186	0.118
EK -> SN -> EI	0.004	0.004	0.003	1.058	0.145
EK -> PBC -> EI	0.157	0.158	0.022	7.055	0.000
IEO -> SN -> EI	0.013	0.013	0.011	1.206	0.114
EK -> PA -> EI	0.035	0.035	0.016	2.200	0.014
IEO -> PBC -> EI	0.051	0.051	0.011	4.786	0.000
EK -> IEO -> EI	0.009	0.009	0.011	0.874	0.191
IEO -> PA -> EI	0.283	0.283	0.023	12.150	0.000

For IEO, the dominant conduit to EI is the attitudinal route. The path IEO → PA → EI is large and highly reliable (β = 0.283, t = 12.150, p < .001), indicating that students with stronger entrepreneurial orientation tend to form more favorable attitudes toward venture creation, and these attitudes, in turn, substantially elevate intention. A smaller but significant channel proceeds through perceived behavioral control (IEO → PBC → EI: β = 0.051, t = 4.786, p < .001), suggesting that entrepreneurial orientation also contributes, to a limited extent, to students' sense of capability and control over starting a business. The normative route is statistically indistinguishable from zero (IEO → SN → EI: β = 0.013, t = 1.206, p = .114), reinforcing the view that perceived social pressure does not meaningfully translate IEO into intention in this cohort. Together, these paths sum to the previously reported total indirect effect of IEO on EI (β = 0.347), and show that orientation is influential chiefly because it strengthens attitude—and, secondarily, perceived control—rather than because it shifts subjective norms.

EK exhibits a multi-branch pattern whose magnitudes align closely with the structural paths. The largest single mediated contribution from EK to EI runs through perceived behavioral control (EK → PBC → EI: $\beta = 0.157$, $t = 7.055$, $p < .001$), consistent with the strong EK → PBC structural link and the substantive PBC → EI effect. The second largest contribution flows through the knowledge-to-orientation-to-attitude chain (EK → IEO → PA → EI: $\beta = 0.096$, $t = 8.130$, $p < .001$), reflecting the mechanism by which knowledge fosters an entrepreneurial orientation that, in turn, elevates attitudes and intention. Smaller yet significant increments arise from EK → PA → EI ($\beta = 0.035$, $t = 2.200$, $p = .014$) and EK → IEO → PBC → EI ($\beta = 0.017$, $t = 4.322$, $p < .001$). By contrast, routes that rely on subjective norms are negligible and non-significant in their final leg (EK → SN → EI: $\beta = 0.004$, $t = 1.058$, $p = .145$; EK → IEO → SN → EI: $\beta = 0.004$, $t = 1.186$, $p = .118$), which is expected given the weak SN → EI coefficient in the structural model. The residual term EK → IEO → EI ($\beta = 0.009$, $t = 0.874$, $p = .191$) is also not significant and simply restates that orientation affects intention only through PA and PBC rather than a direct link. Summing the significant EI-terminal chains yields the total indirect effect EK → EI = 0.322 ($t = 10.218$, $p < .001$), confirming that knowledge raises intention entirely by strengthening attitude and perceived control—directly and via orientation—rather than by altering perceived social approval.

4.2.6.3 Total Effects

The total‐effects estimates summarize the overall influence of each antecedent once both direct and mediated pathways are taken into account. As expected, the proximal beliefs remain the most potent direct drivers of entrepreneurial intention (EI): the total effect of attitude (PA) on EI is $\beta = 0.507$ ($t = 15.970$, $p < .001$), and perceived behavioral control (PBC) has a smaller but still substantive total effect of $\beta = 0.294$ ($t = 8.702$, $p < .001$). In contrast, subjective norms (SN) show a trivial and non-significant total effect on EI ($\beta = 0.036$, $t = 1.222$, $p = .111$), reinforcing the earlier structural result that normative pressure does not translate into intention in this cohort.

Table 13: Total effects

Effect	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
EK -> EI	0.419	0.420	0.028	14.943	0.000
EK -> IEO	0.338	0.339	0.031	10.856	0.000
EK -> PA	0.258	0.258	0.033	7.919	0.000
EK -> PBC	0.593	0.594	0.027	21.600	0.000
EK -> SN	0.224	0.225	0.034	6.599	0.000
IEO -> EI	0.374	0.374	0.031	11.978	0.000
IEO -> PA	0.558	0.558	0.030	18.718	0.000
IEO -> PBC	0.172	0.173	0.031	5.594	0.000
IEO -> SN	0.367	0.367	0.034	10.649	0.000
PA -> EI	0.507	0.507	0.032	15.970	0.000
PBC -> EI	0.294	0.294	0.034	8.702	0.000
SN -> EI	0.036	0.036	0.029	1.222	0.111

Upstream constructs exert sizeable overall influence on EI once their mediated pathways are included. Entrepreneurial knowledge (EK) has a large and highly significant total effect on EI ($\beta = 0.419$, $t = 14.943$, $p < .001$). Comparing this to the previously reported total indirect effect from EK to EI ($\beta = 0.322$) indicates that approximately three quarters of EK's overall impact on intention is mediated through the belief set ($\approx 0.322/0.419 = 76.9\%$), with a modest residual component (≈ 0.10) attributable to either a small direct link or higher-order routes captured in the total. This pattern is consistent with EK's strong total effects on the mediators−EK → PBC ($\beta = 0.593$, $t = 21.600$, $p < .001$), EK → PA ($\beta = 0.258$, $t = 7.919$, $p < .001$), EK → IEO ($\beta = 0.338$, $t = 10.856$, $p < .001$), and EK → SN ($\beta = 0.224$, $t = 6.599$, $p < .001$)−which collectively propagate EK's influence forward to EI, primarily through PA and PBC given their dominant links to intention.

Individual entrepreneurial orientation (IEO) likewise demonstrates a strong overall association with EI once mediation is considered: the total effect IEO → EI is $\beta = 0.374$ ($t = 11.978$, $p < .001$). Because IEO's total indirect effect on EI was $\beta = 0.347$, roughly nine tenths of its total influence is carried through the mediators (≈ 92.8%), especially via attitude, which it affects robustly (IEO → PA $\beta = 0.558$, $t = 18.718$, $p < .001$). Smaller but significant total effects from IEO to PBC ($\beta = 0.172$, $t = 5.594$, $p < .001$) and to SN ($\beta = 0.367$, $t = 10.649$, $p < .001$) indicate that orientation also shapes perceived capability and normative perceptions, although the latter channel contributes little to intention because SN has a weak link to EI in this sample.

The mediation analysis shows that entrepreneurial knowledge (EK) and individual entrepreneurial orientation (IEO) influence entrepreneurial intention (EI) chiefly by reshaping the TPB belief set—most notably attitude (PA) and perceived behavioral control (PBC). The total indirect effect from EK to EI is sizeable ($\beta = 0.322$, $t = 10.218$, $p < .001$), while IEO's total indirect effect is similarly strong ($\beta = 0.347$, $t = 13.360$, $p < .001$). Decomposition of specific paths clarifies the mechanism. For IEO, the dominant conduit is the attitudinal route (IEO → PA → EI, $\beta = 0.283$, $t = 12.150$, $p < .001$), complemented by a smaller but significant efficacy route (IEO → PBC → EI, $\beta = 0.051$, $t = 4.786$, $p < .001$). The normative branch (IEO → SN → EI) is not statistically different from zero ($\beta = 0.013$, $t = 1.206$, $p = .114$), indicating that perceived social pressure does not transmit the effect of orientation onto intention in this cohort.

EK exhibits a multi-branch pattern aligned with the structural paths. The largest single mediated contribution proceeds through perceived control (EK → PBC → EI, $\beta = 0.157$, $t = 7.055$, $p < .001$), consistent with the strong EK → PBC path and the substantive PBC → EI link. A second, theory-congruent chain runs knowledge → orientation → attitude → intention (EK → IEO → PA → EI, $\beta = 0.096$, $t = 8.130$, $p < .001$). Smaller but significant increments arise via EK → PA → EI ($\beta = 0.035$, $t = 2.200$, $p = .014$) and EK → IEO → PBC → EI ($\beta = 0.017$, $t = 4.322$, $p < .001$). By contrast, routes that terminate through norms are negligible (EK → SN → EI, $\beta = 0.004$, $t = 1.058$, $p = .145$; EK → IEO → SN → EI, $\beta = 0.004$, $t = 1.186$, $p = .118$), which is expected given the weak and non-significant SN → EI path in the structural model. The residual EK → IEO → EI component is also non-significant (β = 0.009, t = 0.874, p = .191), reaffirming that orientation affects intention only via PA and PBC rather than directly.

Viewed alongside the total effects, these results imply that most of EK's overall association with EI is mediated through beliefs (≈ 0.322/0.419 ≈ 77%), and virtually all of IEO's total influence is mediated (≈ 0.347/0.374 ≈ 93%). Substantively, the mediation pattern isolates PA and PBC as the active levers linking upstream enablers (knowledge and orientation) to intention, while subjective norms do not carry meaningful influence once PA and PBC are considered.

4.2.7 Multi-Group Analysis (permutation MGA)

4.2.7.1Age Group

We assessed measurement invariance across age groups (17–22 vs. 23–28) using the MICOM procedure in SmartPLS 4. Configural invariance was ensured by using identical indicators, data treatment, and algorithm across groups. Compositional invariance (Step 2) was established for all constructs (permutation p's > .05; original correlations ≈1.00), thereby fulfilling the requirement for partial measurement invariance and legitimizing cross-group comparisons. Step 3 indicated equality of variances (all p's > .09) but revealed mean differences for EK (Δ=−.153, p=.018), IEO (Δ=+.196, p=.004), and PBC (Δ=−.133, p=.048), whereas EI, PA, and SN did not differ by age (p's > .25).

Permutation-based MGA compared structural paths across age groups. Three paths significantly differed: EK→IEO was stronger for 23–28 (β=.418) than 17–22 (β=.265; Δ=−.153, p=.015), EK→SN was stronger for 17–22 (β=.198) than 23–28 (β=.019; Δ=+.179, p=.014), and PBC→EI was stronger for 23–28 (β=.403) than 17–22 (β=.293; Δ=−.110, p=.029). Differences for other paths, including IEO→PA, were not significant (p≥.09). These results suggest that with increasing age, entrepreneurial knowledge more effectively builds both orientation (IEO) and perceived control (PBC), and perceived control more strongly translates into intention; in contrast, younger students' knowledge is more associated with perceptions of normative support, though subjective norms do not directly predict intention in either group.

4.2.7.2 University Type

Measurement invariance across university type (International vs. Private) was assessed using MICOM in SmartPLS 4. Configural invariance was ensured via identical measurement and estimation settings. In Step 2 (compositional invariance), EI, PA, and PBC exhibited p-values > .05, whereas EK (p=.038), IEO (p=.003), and SN (p<.001) did not SN showed a particularly low cross-group composite correlation (c=.287). Hence, partial measurement invariance was not achieved for the full model. Step 3 revealed sizable mean differences across groups for all constructs (all p<.001) and some variance differences (e.g., EI, SN), but given Step-2 failures, these differences are interpreted descriptively rather than inferentially.

4.2.7.3 Academic Year

Measurement invariance across academic year (3rd vs. 4th) was assessed via MICOM in SmartPLS 4. Configural invariance was ensured by identical measurement and estimation settings. Compositional invariance (Step 2) was established for all constructs (permutation p's > .05), satisfying partial measurement invariance and permitting cross-group comparisons. Step 3 indicated equality of variances (all p's ≥ .27) but mean differences for PBC (Δ=−.181, p=.036) and SN (Δ=+.176, p=.042); EI, EK, IEO, and PA means did not differ (p≥.13). Permutation-based MGA detected no significant differences in any structural relation (all p≥.17), indicating that the paths determining EI operate similarly across years. Thus, academic year is associated with level differences—lower perceived control and higher subjective norms among 3rd-year students—but not with changes in the underlying structural process linking EK, IEO, PA, PBC, SN, and EI.

Similarly, MICOM across academic year (4th vs. 1st) indicated configural invariance and compositional invariance for all constructs (Step 2 p's > .05), establishing partial measurement invariance and permitting cross-group comparisons. Step 3 showed mean differences for IEO (Δ=+0.200, p=.024; higher in 1st year) and PBC (Δ=−0.176, p=.038; lower in 1st year), with marginal PA (p=.063) and no differences for EI, EK, or SN; several variance differences were observed (EK, PBC, SN). Permutation-based MGA detected a single significant path difference: EK→SN was stronger in 1st year than 4th (Δ=+0.196, p=.044). All other structural paths, including PA→EI and PBC→EI, were statistically equivalent across groups (p≥.09), indicating that the mechanism generating EI is stable by academic stage, with early students more likely to map knowledge onto perceived normative support.

4.2.7.4 Preliminary Questions

Measurement invariance across business ownership was evaluated with MICOM (Owners vs Non-owners) in SmartPLS 4. Configural invariance was ensured by identical measurement and estimation settings. Compositional invariance (Step 2) was established for all constructs (permutation p's > .05), satisfying partial measurement invariance and permitting cross-group comparisons. Step 3 indicated mean differences favoring owners on EI, EK, PA, and PBC (all p<.01), with unequal variances for EK and PBC but not for the other constructs. Permutation-based MGA revealed a single significant path difference: EK→IEO was stronger for owners (β=.559) than non-owners (β=.293; Δ=+.266, p=.001). All other structural paths, including PA→EI and PBC→EI, did not differ significantly between groups (p's ≥ .06). These results suggest that while the proximal determinants of intention (attitude, perceived control, norms) operate similarly, business ownership amplifies the conversion of knowledge into entrepreneurial orientation.

We tested measurement invariance across students whose families own a business (Yes vs. No) using MICOM in SmartPLS 4. Configural invariance was ensured by identical measurement and estimation settings. Compositional invariance (Step 2) held for EI, EK, IEO, PA, and SN (p's > .05) but not for PBC (p = .015); thus, partial measurement invariance for the full model was not achieved. Step 3 indicated higher means for EI, EK, and SN in the "Yes" group (all p ≤ .006); PBC was also higher but cannot be interpreted inferentially given Step-2 failure. Permutation-based MGA showed no significant differences for paths among invariant constructs (EK→IEO, EK→PA, EK→SN, IEO→PA, IEO→SN, PA→EI, SN→EI; all $p \geq .215$). Paths involving PBC (EK→PBC, IEO→PBC, PBC→EI) were treated as exploratory and were also non-significant. Overall, family business background is associated with higher levels of knowledge, norms, and intention, but the structural relations among EK, IEO, PA, SN, and EI appear stable across groups.

Measurement invariance across students with and without entrepreneurship training was assessed with MICOM in SmartPLS 4. Configural invariance was ensured via identical measurement and estimation procedures. Compositional invariance (Step 2) was established for all constructs (p's > .05), satisfying partial measurement invariance and permitting cross-group comparisons. Step 3 indicated higher means for EI, EK, IEO, and PBC among trained students (all $p \leq .001$), with no mean differences for PA or SN; variances differed for EI, PBC, and SN. Permutation-based MGA detected no significant differences in any structural path (all $p \geq .143$), indicating that the process by which knowledge, orientation, attitude, perceived control, and norms shape entrepreneurial intention operates similarly regardless of training exposure. Training therefore appears to shift levels (especially EK and PBC) rather than alter causal sensitivities among constructs.

4.2.8 Importance–Performance Map Analysis (IPMA)

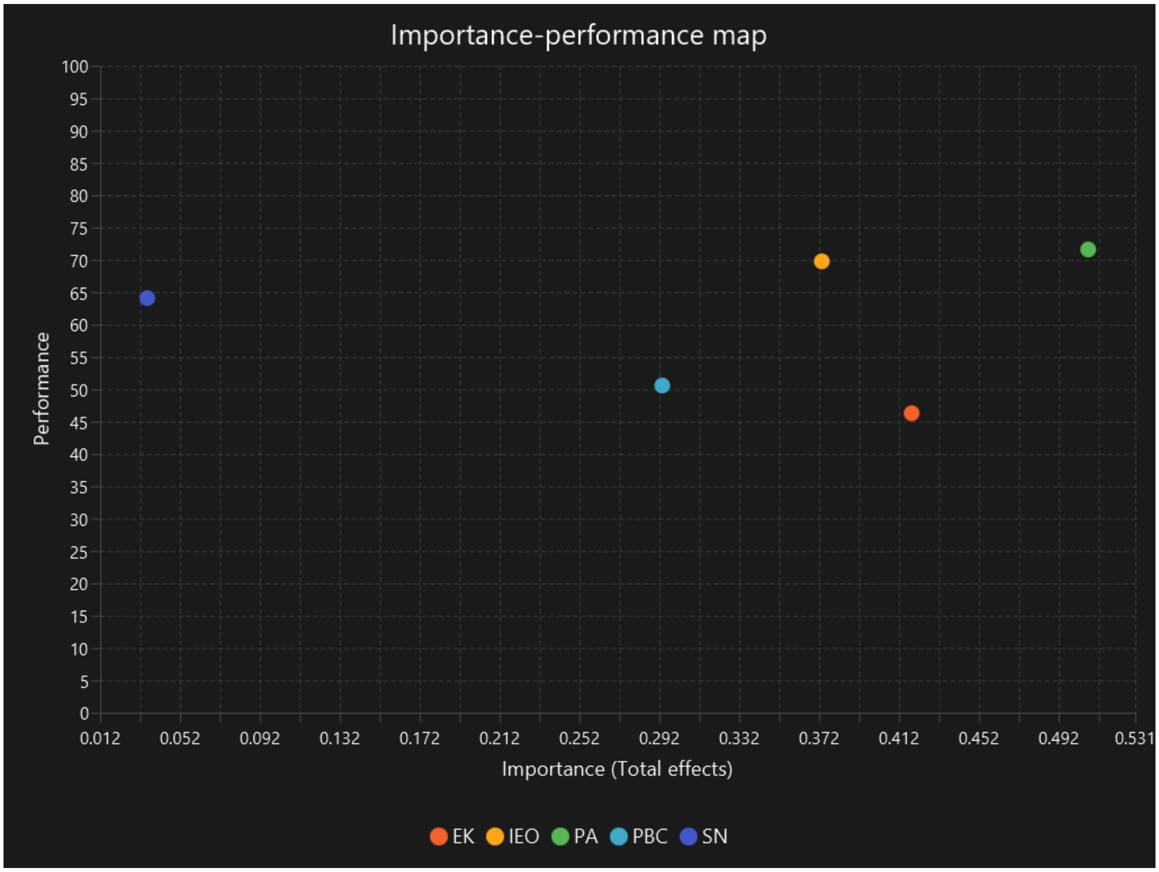

Figure 8: Importance–Performance Map for Contructs

Importance-Performance Map Analysis (IPMA; target = EI) identified perceived behavioral control (PBC) and entrepreneurial knowledge (EK) as priority levers—both exhibits above-average importance (β_total ≈ .35) but below-average performance (PBC = 50.6; EK = 46.3). Attitude (PA) shows the highest importance (.524) and high performance (71.6), while entrepreneurial orientation (IEO) performs strongly (69.8) at moderate importance (.367); subjective norms (SN) display low importance (.039). At the indicator level, the highest-leverage shortfalls lie in EK3, EK4, EK1 and PBC3, PBC4 (importance ≥ .091; performance ≤ 53), with secondary opportunities in EK2, PBC2, PBC5, PBC1. IEO is generally strong but IEO2 and IEO6 have comparatively lower performance. These results suggest concentrating interventions on PBC and EK to maximize gains in EI, while maintaining high PA and IEO levels and deprioritizing SN.

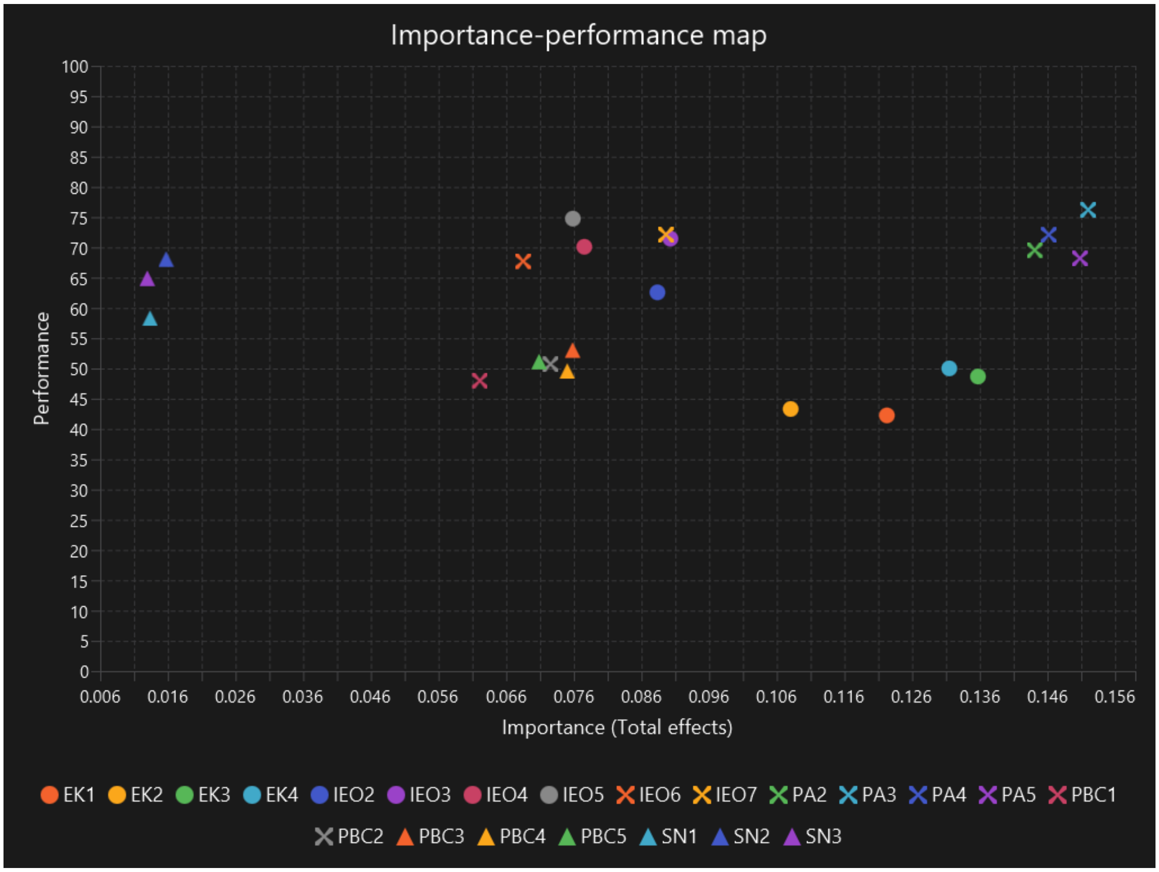

Figure 9: Importance–Performance Map for Items

4.3 Machine Learning Analysis Report (Aligned to SEM)

This section reports a rigorous machine learning (ML) analysis designed to complement and cross-validate the structural equation modeling (SEM) findings on predictors of entrepreneurial intention (EI) among computer science students. The ML pipeline uses composite features constructed from the SEM-trimmed measurement model (IEO1, PA1, and PBC6 removed) to ensure a one-to-one alignment between explanatory (SEM) and predictive (ML) perspectives. We benchmark seven models with five-fold cross-validation (CV) and model-specific tuning, apply a one-standard-error selection rule for parsimony, and use SHAP explainability to relate predictive importance back to the SEM's theoretical paths.

4.3.1 Data & Features (Aligned to SEM)

We computed composite scores as the mean of retained items for each construct: Knowledge (EK_avg), Entrepreneurial Orientation (IEO_avg), Attitude (PA_avg), Perceived Behavioral Control (PBC_avg), Subjective Norms (SN_avg), and the target Entrepreneurial Intention (EI_avg). The dataset contains N = 929 complete records on 1–7 Likert scales.

Descriptive Statistics & Reliability

Table 14: Descriptive statistics and internal consistency for composites

Construct	Mean	SD	N	Cronbach's alpha
EK_avg	3.7637	1.6081	929	0.8596
IEO_avg	5.1875	1.2865	929	0.8517
PA_avg	5.2906	1.5166	929	0.8738
PBC_avg	4.0297	1.4670	929	0.8763
SN_avg	4.8260	1.5226	929	0.7697
EI_avg	4.9121	1.5522	929	0.9134

Interpretation. All composites demonstrate acceptable to excellent reliability ($\alpha \geq .77$), with the intended outcome scale (EI) exhibiting the highest internal consistency ($\alpha \approx .91$). Central tendencies for PA and IEO are above the neutral midpoint, while EK and PBC are closer to the midpoint, reflecting realistic variability in knowledge and perceived control.

4.3.2 Models, Tuning, and Validation

We evaluated Linear Regression, Ridge, Decision Tree, Random Forest, XGBoost (with theory-aligned monotonic constraints), SVR (RBF kernel), and MLP. Preprocessing (median imputation and scaling as appropriate) was embedded in each pipeline and performed within folds to avoid leakage. Five-fold CV with GridSearchCV was used for model-specific hyperparameter tuning. Performance was summarized by RMSE, MAE, and R^2 (mean ± SE across folds), with 95% confidence intervals (CI) for RMSE.

Cross-Validated Performance (5-fold CV with tuning)

Table 15: Five-fold cross-validated performance with tuning

Model	**RMSE (mean ± SE)**	**RMSE 95% CI**	**MAE (mean ± SE)**	**R^2 (mean ± SE)**
XGBRegressor	0.999 ± 0.046	[0.907, 1.090]	0.745 ± 0.014	**0.580 ± 0.029**
Random Forest	1.015 ± 0.037	[0.943, 1.087]	0.761 ± 0.008	0.574 ± 0.025
SVR (RBF)	1.017 ± 0.070	[0.880, 1.155]	0.742 ± 0.023	0.572 ± 0.038
Ridge	1.030 ± 0.072	[0.890, 1.171]	0.763 ± 0.020	0.567 ± 0.039
Linear Regression	1.030 ± 0.072	[0.888, 1.172]	0.762 ± 0.020	0.567 ± 0.039
MLP	1.051 ± 0.043	[0.967, 1.135]	0.772 ± 0.016	0.559 ± 0.027
Decision Tree	1.092 ± 0.032	[1.028, 1.155]	0.806 ± 0.015	0.543 ± 0.018

Interpretation. XGBRegressor achieved the lowest RMSE on average; however, Random Forest and SVR were statistically comparable within sampling error. Linear and Ridge baselines performed closely to the best model. Overall explained variance clustered around $R^2 \approx .56–.58$, which closely matches the SEM's R^2 for EI (≈.572), indicating convergence between predictive ML and the explanatory SEM model.

4.3.3 Parsimonious Selection (One-Standard-Error Rule)

Using the one-standard-error (1-SE) rule with the best RMSE (0.999 ± 0.046; threshold 1.045), the following models fall within the parsimony band: Linear Regression, Ridge, SVR (RBF), Random Forest, and XGBRegressor. We therefore select Linear Regression as the primary model for reporting due to interpretability and comparable generalization error.

Table 16: Parsimony candidates under the 1-SE criterion

Model (within 1-SE)	RMSE (mean ± SE)	R^2 (mean ± SE)
Linear Regression	1.030 ± 0.072	0.567 ± 0.039
Ridge	1.030 ± 0.072	0.567 ± 0.039
SVR (RBF)	1.017 ± 0.070	0.572 ± 0.038
Random Forest	1.015 ± 0.037	0.574 ± 0.025
XGBRegressor	0.999 ± 0.046	0.580 ± 0.029

4.3.5 Explainability: SHAP Global Importance

To align ML insights with SEM theory, we used SHAP to quantify feature contributions. The summary plot (Figure ML-1) shows a clear ranking: PA_avg > PBC_avg >> EK_avg ≈ SN_avg ≈ IEO_avg. High PA and PBC values consistently pushed EI predictions upward, while EK contributed modestly and SN/IEO had near-zero direct contributions. This pattern is coherent with the SEM structural paths: PA→EI strongest ($\beta \approx .524$), PBC→EI moderate ($\beta \approx .353$), SN→EI negligible ($\beta \approx .039$, $p=.175$), and EK's influence largely indirect via IEO→PA and PBC.

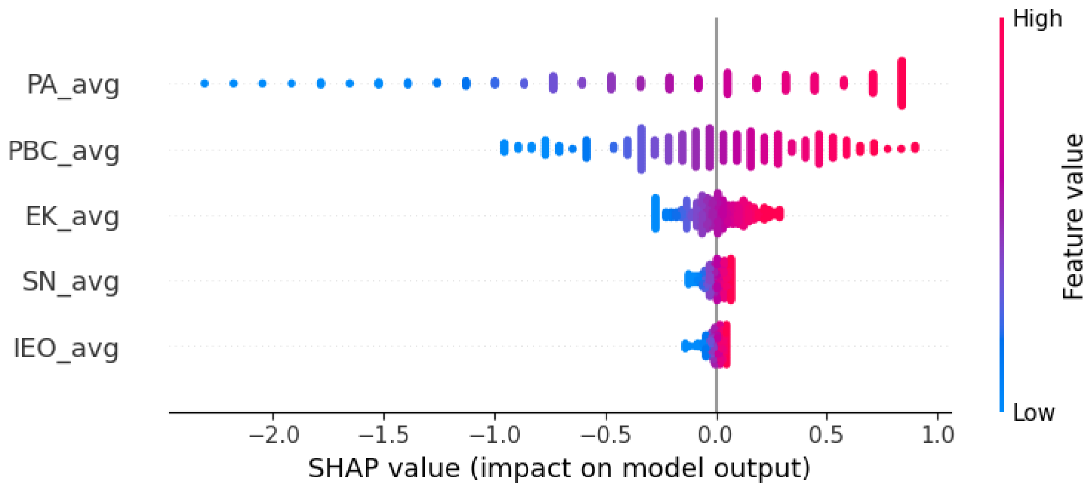

Figure 10: SHAP summary plot for the predictive model. Higher PA and PBC increase EI; EK is small; SN and IEO contribute negligibly

4.3.6 A Priori Ablation: Subjective Norms (SN)

Given the SEM's non-significant SN→EI path, we ablated SN from the ML features. Linear regression was unaffected (RMSE 1.0303 → 1.0296; Δ≈0.07%). For boosted trees, excluding SN and correcting monotonic constraints to match the 4-feature set substantially improved accuracy. A tuned XGB model without SN achieved RMSE = 1.009 ± 0.056 (95% CI [0.898, 1.119]) with best parameters {n_estimators=500, learning_rate=0.01, max_depth=5, subsample=1.0, colsample_bytree=1.0}. A paired test on foldwise RMSEs showed no significant improvement over Linear ($t=0.847$, $p=0.445$), so we retain Linear as the primary model for parsimony and present XGB(no-SN) as a robustness check.

Table 17: Subjective Norms ablation and targeted XGB tuning results

Model / Configuration	RMSE (5-fold)	Δ vs. with-SN	Notes
Linear Regression (with SN)	1.03033	—	Baseline, 5 features
Linear Regression (no SN)	1.02960	−0.00073 (~0.07%)	No practical change
XGB (fixed config, with SN)	1.22563	—	Constraint length includes SN (5 features)
XGB (fixed config, no SN)	1.02760	−0.19803 (~16%)	Constraint corrected to 4 features
XGB (tuned, no SN)	1.009 ± 0.056	—	95% CI [0.898, 1.119]; best params listed above

Table 18: Paired test of top parsimonious models

Paired comparison (foldwise RMSE)	t	p	Conclusion
Linear (no SN) vs. XGB (tuned, no SN)	0.847	0.445	No significant difference; prefer parsimonious Linear

4.3.7 Linking ML Back to SEM

The ML hierarchy (PA > PBC >> EK ≈ SN ≈ IEO) mirrors the SEM's structural estimates (PA→EI strongest; PBC→EI moderate; SN→EI non-significant). EK's small direct predictive effect in ML aligns with SEM's strong indirect effects: EK→PBC (β≈.536) and EK→IEO (β≈.337), followed by IEO→PA (β≈.557), yielding sizable mediated contributions to EI via PA and PBC. Importantly, ML and SEM explain a similar share of variance in EI (R^2≈.56–.58 ML, R^2≈.572 SEM), demonstrating robust triangulation between explanatory and predictive perspectives.

4.3.8 Robustness & Reproducibility Notes

Robustness. Results are stable across algorithms and insensitive to inclusion of SN in linear models; complex learners offer only modest, statistically non-decisive gains. As an additional check, the optional nested CV (5×5 repeats) can be executed to verify the error envelopes.

Reproducibility. All analyses were conducted with fixed random seeds and saved grids. The accompanying Colab notebook includes code to regenerate all tables and the SHAP figure.

4.4 Discussion

The current study provides valuable insights into the levels and determinants of entrepreneurial intention among Computer Science and Engineering (CSE) students in Bangladesh. The findings address two critical research questions regarding the current state of entrepreneurial intentions and the psychological and contextual factors influencing these intentions within this specific population.

This chapter integrates the findings from structural equation modeling (SEM) and machine learning (ML) to answer the study's research questions (RQs) on entrepreneurial intention (EI) among computer science and engineering (CSE) students in Bangladesh. We emphasize where the two approaches converge, where they differ, and how the combined evidence can inform education and policy.

4.4.1 RQ1. What is the current level of entrepreneurial intention among CSE students in Bangladesh?

The descriptive statistics based on the SEM-trimmed composites show a moderate-to-high level of EI in the sample ($N = 929$): EI_avg $M = 4.91$, $SD = 1.55$ on a 1–7 scale; median = 5.17; 25th–75th percentiles = 4.00–6.17. This distribution indicates that most students score at or above the neutral midpoint, suggesting a sizeable pool of latent entrepreneurial interest.

4.4.2 RQ2. How do psychological and contextual factors relate to entrepreneurial intention (SEM results)?

Consistent with the Theory of Planned Behavior and the hybrid model specified, attitude toward entrepreneurship (PA) and perceived behavioral control (PBC) emerged as the dominant proximal predictors of EI. The structural paths were: PA→EI $\beta = 0.524$ ($p < .001$), PBC→EI $\beta = 0.353$ ($p < .001$), while subjective norms (SN) → EI was non-significant ($\beta = 0.039$, $p = .175$). Entrepreneurial knowledge (EK) exerted strong upstream effects on PBC ($\beta = 0.536$, $p < .001$) and on entrepreneurial orientation (IEO; $\beta = 0.337$, $p < .001$), with a smaller direct link to PA ($\beta = 0.070$, $p = .024$). IEO, in turn, substantially shaped PA ($\beta = 0.557$, $p < .001$). The model explained a large share of variance in EI ($R^2 = 0.572$), with meaningful variance also explained in PA ($R^2 = 0.342$), PBC ($R^2 = 0.378$), and SN ($R^2 = 0.169$).

Mediation tests reinforced this structure: EK's total indirect effect on EI was $\beta = 0.353$ ($p < .001$), primarily via the chains EK→PBC→EI ($\beta = 0.189$) and EK→IEO→PA→EI ($\beta = 0.098$). IEO's total indirect effect on EI was $\beta = 0.367$ ($p < .001$), largely through IEO→PA→EI ($\beta = 0.292$). These results indicate that knowledge and entrepreneurial orientation matter chiefly because they shape attitude and perceived control, which are the immediate determinants of intention in this cohort.

4.4.3 RQ3. To what extent can machine learning accurately predict entrepreneurial intention?

Seven regressors (Linear, Ridge, Decision Tree, Random Forest, XGBoost with theory-consistent monotonicity, SVR-RBF, MLP) were tuned and evaluated with 5-fold cross-validation. The best point estimate was achieved by XGBoost (RMSE = 0.999 ± 0.046; $R^2 \approx 0.580$), closely followed by Random Forest and SVR. Linear and Ridge were only modestly behind (RMSE ≈ 1.030; $R^2 \approx 0.567$–0.568). Under the one-standard-error rule, Linear Regression falls within the parsimony band and was selected for primary reporting. A targeted sensitivity run excluding SN (given its non-significant SEM path) yielded XGB(no-SN) RMSE = 1.009 ± 0.056 (95% CI [0.898, 1.119]); a paired test on foldwise RMSEs showed no significant improvement over Linear ($t = 0.847$, $p = 0.445$). We conclude that ML can predict EI with accuracy comparable to SEM's explained variance, but complex models do not significantly outperform linear baselines for this dataset.

4.4.4 RQ4. Which variables emerge as the strongest predictors in the ML model?

Explainability diagnostics (SHAP) on the predictive models converge on the ranking PA_avg > PBC_avg >> EK_avg ≈ IEO_avg ≈ SN_avg. High PA and PBC values consistently push EI predictions upward (monotonic pattern), while EK and IEO contribute only modestly to direct prediction and SN is near zero. Importantly, this mirrors the SEM: PA and PBC are the proximal drivers, whereas EK and IEO exert influence primarily indirectly by shaping PA and PBC. The SHAP summary should be placed as Figure D-1 immediately after Table D-2.

4.4.5 RQ5. How do SEM and ML compare?

First, convergence: both frameworks agree that attitude and perceived control are the principal antecedents of entrepreneurial intention, and that subjective norms contribute little directly. Second, variance explained is highly similar (SEM R^2 for EI = 0.572; ML $R^2 \approx 0.56$–0.58), and PLSpredict diagnostics indicated no advantage of linear benchmarking over the PLS model. Third, mediation vs. direct prediction: SEM explicitly decomposes EK and IEO into mediated pathways through PA and PBC; ML reproduces the same practical pattern through SHAP importance without claiming causal mediation. Fourth, parsimony: complex ML models deliver modest point improvements that are not statistically decisive under the one-standard-error rule; hence, a linear predictive specification is sufficient for generalization in this context.

4.4.6 RQ6. How should these insights inform education and policy?

We synthesize implications using the Importance–Performance Map Analysis (IPMA) and subgroup diagnostics. IPMA highlighted high importance for PA (effect on EI = 0.524) and PBC (0.353), with current performance higher for PA (≈71.6) than for PBC (≈50.6). EK has meaningful importance (total effect on EI = 0.353) but lowest performance (≈46.3). IEO shows high performance (≈69.8) and moderate importance (0.367), whereas SN is low importance (0.039).

Actionable recommendations: (1) Build PBC through mastery-oriented, skills-heavy modules (prototype labs, venture sprints, seed-funded capstones, mentoring) that increase self-efficacy and control over entrepreneurial tasks; (2) Raise EK via modular micro-credentials on opportunity recognition, legal/finance, go-to-market, and fundraising; (3) Leverage IEO to lift PA through challenge-based learning (hackathons, incubator residencies) that foster proactiveness and innovativeness—mechanisms shown by SEM (IEO→PA) to translate into intention; (4) De-emphasize SN as a direct lever but consider it as a supportive climate outcome of the above changes; (5) Target subgroups: for students in international universities, EK→PBC and EK→PA effects were stronger, suggesting knowledge-centric programming pays off; for business owners, EK→IEO was stronger, implying orientation-shaping modules can channel existing knowledge into attitudes; older students showed stronger PBC→EI, so interventions that convert competence into action (e.g., venture launch studios) are likely to be effective.

4.4.7 Heterogeneity & Measurement Invariance (MICOM/MGA)

MICOM supported compositional invariance for most groups, with localized exceptions (e.g., PBC across family-business status, and SN across university type). Multi-group path comparisons revealed theoretically meaningful differences: older students showed a stronger PBC→EI path; international-university students exhibited stronger EK→PBC and EK→PA, while private-university students relied more on IEO→PA and IEO→SN; those who already own a business had a markedly stronger EK→IEO path. These patterns underscore the value of tailoring program components to institutional context and student profile.

4.4.8 Limitations and Future Research

First, the cross-sectional design precludes causal claims; longitudinal or experimental designs could test whether boosting EK or PBC causes sustained gains in EI. Second, self-report measures may introduce common-method bias despite strong reliability; incorporating behavioral indicators (e.g., venture submissions, prototype completions) would strengthen validity. Third, while model fit and multicollinearity diagnostics were acceptable (e.g., SRMR≈0.076; all indicator VIFs < 3.1), some measurement invariance issues suggest caution when comparing certain subgroups. Finally, while ML showed no decisive advantage over linear baselines, future work might explore richer features (text from project logs, mentorship networks) and external validation across institutions.

4.4.9 Conclusion

Across SEM and ML, a coherent picture emerges: attitude and perceived behavioral control are the primary, convergent determinants of entrepreneurial intention among Bangladeshi CSE students. Entrepreneurial knowledge and orientation matter because they raise PA and PBC, not because they directly drive intention. Predictive accuracy from ML matches SEM's explanatory power; given the negligible contribution of SN, parsimonious linear models suffice for generalization. For practice, the highest-yield levers are clear: lift PBC and EK, maintain strong PA through orientation-rich experiences, and tailor interventions to subgroup profiles and institutional context..

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

The Computer Science and Engineering (CSE) students in Bangladesh and their entrepreneurial desires/work have proven to have a high potential to have an impact on the social and economic growth. The conclusions of this research are in line with the idea that the entrepreneurial spirit of these students is mainly determined by personal skills and self-confidence as well as personal attitudes, as opposed to social influences. These trends imply the creation of a new technological-based entrepreneurship paradigm that can potentially have a transformative effect on the society of Bangladesh.

CSE graduates are poised to generate high value jobs as they move into the sphere of entrepreneurship, which will help in the economic development of the countries outside conventional sectors. Their initiatives will be able to drive innovation and develop an entrepreneurial ecosystem based on knowledge, which will, consequently, enhance the competitiveness of the country.

In social terms, technology entrepreneurship offers innovative solutions to the burning problems within the society. Healthcare accessibility, educational technology, financial inclusion, and the productivity of agriculture are some of those areas that will have a lot of gains. As an illustration, the services can be better delivered through digital platforms and applications created by entrepreneurial CSE graduates, which will also improve the connectivity and efficient allocation of resources. Additionally, these technological solutions can eliminate the urban-rural digital disparity because they will broaden digital access to underserved populations, thus allowing more inclusive development.

Also, student-led ventures, when successful, can serve as an inspiration to the future generation as it builds on the cultural perception of what entrepreneurship should be. The success stories of entrepreneurs can ultimately contribute to changing the attitude of the society and make entrepreneurship not only a dangerous but a prestigious and good career choice.

5.2 Impact on the Environment

Technology based entrepreneurship has a significant effect on the environment that is worth consideration. CSE graduates have a rare opportunity to come up with sustainable technologies and environmental solutions that support the current environmental problems. Such innovations can be directly related to the fulfillment of the national and global sustainability goals, starting with energy-efficient computing systems and waste management applications, up to tools that will enable monitoring of the climate.

Moreover, these results have significant implications of gender. As this paper shows, individual skills and confidence seem to have a greater role than the social expectations in influencing entrepreneurship intentions. As a result of this change, feminist CSE pupils have more chances to become entrepreneurs and the effect of conventional social values, which frequently limit the career opportunities of women, is minimized. In the long-term, it would help to encourage gender diversity in technology leadership, transform how society views women in business, and create more equal engagement in economic development.

Further, innovation culture can be cultivated to increase global competitiveness of Bangladesh. With innovative solutions offered by entrepreneurial CSE graduates, they will be able to attract international investments and collaborations, which also leads to knowledge transfer and cultural exchange that further benefit the social-economic environment in the country.

5.3 Ethical Aspects

This research adhered to strict ethical standards. Approval was obtained from the Daffodil International University Board of Examiners, and all participants provided informed consent prior to involvement. Measures were taken to maintain data confidentiality and anonymity throughout the study to ensure participants' rights and privacy were fully protected.

5.4 Sustainability Plan

CSE entrepreneurs can play a key, critical role in advancing the ideals of the circular economy. They can do this with innovative software and hardware designs to increase the life of the products, ease repair and reuse of products and increase the recycling of the electronic products, hence minimizing the environmental footprint of electronic products.

There are considerable opportunities in matters of energy efficient computing, green data centers and sustainable electronics manufacturing, which are crucial in ensuring that the state of the technological advancement does not come at the ecological health cost.

Moreover, the entrepreneurship based on technology will be able to empower the local populations to engage in the environmental stewardship. For example:

1. Online platforms are capable of creating awareness in society concerning environmental problems.
2. Air and water quality can be monitored by the mobile applications.
3. Communal conservation may be facilitated through citizen science projects.

The entrepreneurial vision of CSE students, who combine technical knowledge with entrepreneurial skills, will help solve environmental problems and create the sustainability culture in the society.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

This research explored the determinants of entrepreneurial intentions among Computer Science and Engineering students in Bangladesh, drawing on the Theory of Planned Behavior (TPB) alongside additional factors such as entrepreneurial knowledge and personal orientation. The study aimed to assess the current level of entrepreneurial motivation among CSE students and to investigate the influence of attitudes, subjective norms, perceived behavioral control, and individual knowledge on their entrepreneurial aspirations.

6.2 Conclusions

This study shows that entrepreneurial intention among Bangladeshi CSE students is generally above the midpoint, and is driven chiefly by attitude toward entrepreneurship and perceived behavioral control. Entrepreneurial knowledge and entrepreneurial orientation matter because they raise those beliefs most notably attitude and self-efficacy rather than exerting strong direct effects, while subjective norms play little role once attitude and control are accounted for. Machine-learning results corroborate the structural model: predictive accuracy ($R^2 \approx .56 - .58$) matches the SEM's explained variance, and the most parsimonious linear specification performs on par with more complex learners; SHAP analyses similarly place attitude and control at the top of the predictive hierarchy. Taken together, the evidence points to practical levers for universities and policymakers: strengthen perceived control through mastery-oriented, skills-based training; deepen entrepreneurial knowledge with targeted, modular content; and use orientation-building experiences to elevate attitudes. Tailoring these elements to institutional and student profiles indicated by subgroup differences should further enhance impact.

6.3 Implications for Future Research

This study opens several avenues for further investigation:

Longitudinal Research

Future studies could track CSE students over time to examine how their entrepreneurial intentions evolve as they transition into professional roles. Such research would provide insights into the factors that enable or hinder the translation of entrepreneurial intent into actual behavior.

Mixed-Methods Approaches

Combining quantitative surveys with qualitative interviews or focus groups could offer deeper insights into students' challenges, motivations, and lived experiences. This would be especially valuable in understanding why subjective norms exert limited influence in this context.

Cross-Disciplinary Comparisons

Extending the research to include students from other academic fields such as business, social sciences, or life sciences would enable comparative analysis, helping identify whether these findings are unique to CSE students or broadly applicable.

Role of Moderators and Mediators

Future research should examine how factors such as gender, socioeconomic background, prior entrepreneurial exposure, and access to resources influence entrepreneurial intentions. For example, exploring the interaction between gender and perceived capability could shed light on issues of inclusivity in entrepreneurial education.

Contextual Influences

Investigating the role of university support systems, mentorship programs, and digital platforms could provide valuable insights into how institutional and technological environments shape entrepreneurial development. Evaluating the effectiveness of interventions such as entrepreneurship courses, incubators, and industry partnerships would further strengthen understanding in this area.

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