Developing a University–Industry Cooperation Model in Semiconductor Workforce Training in Vietnam: A Mixed-Methods Approach

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Abstract: **-** The semiconductor industry is increasingly treated as a strategic sector, and in Vietnam this has brought attention to workforce issues, although the difficulty does not seem to lie only in the number of trained individuals but also in how training connects, or sometimes fails to connect, with technological and investment demands that continue to change. Using data from 265 respondents drawn from students, lecturers, and enterprise representatives, the analysis looks at how different elements within training systems relate to outcomes, rather than treating these elements separately, which makes the relationships less direct than they initially appear. From the data, it becomes noticeable that elements such as industry engagement, program quality, and skill development do not really operate on their own, and this is not entirely unexpected, but they tend to come together through the way the curriculum adjusts to technological change, which in some cases appears to function as a connecting point rather than a distinct component, even though this distinction is not always very clear. This does not look entirely consistent when different groups are compared, and the variation that appears is not always easy to interpret, because in some cases it reflects differences in how outcomes are understood rather than the outcomes themselves, which makes the issue of alignment more complicated than it first seems, or at least less direct. The role attributed to the State shows a similar pattern, where its influence does not always translate into direct effects, and this is not entirely surprising, but seems to depend on how coordination is carried out, which can support the system in some situations while limiting flexibility in others, although these effects are not always clearly separated. Looking across these patterns, improving training effectiveness seems to depend not only on individual elements, but also on how these elements are arranged and connected, and this point appears repeatedly in the analysis, including how competencies are defined and how collaboration is structured, although the way these relationships form does not follow a single or stable pattern.

Key-Words: - University, Enterprise, Cooperation, Semiconductor, Workforce training, Higher education.

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1 Introduction

The semiconductor industry is now at the forefront of technological capability and competitive advantage at the nation level as the rest of the economy is going through rapid digitalisation and supply chain transformation, [1], [2]. The wave of new products and services that are dependent on semiconductors and integrated circuit systems such as electric vehicles, artificial intelligence, internet of things, 5G telecommunications and many others made up of chips, all require a globally distributed but technically qualified workforce at all levels: production technicians, semiconductor engineers, as well as software and system design engineers and scientists, [1], [2]. There is an emerging global reallocation of manufacturing investment and R&D effort into this vital sector, [1], [3].

Investments in new innovative infrastructure and human resources have for several decades been considered as important elements of innovation policy in several countries. The US CHIPS and Science Act of 2022 for example contains a large allocation to basic and applied research as well as semiconductor fabrication, as well as university–industry training programs, [4], [5]. Currently there are large joint investments by industry and universities in the Netherlands in the development of the semiconductor ecosystem: by semiconductor equipment manufacturer ASML in high-tech education and research in the field of semiconductor technology in combination with Silicon Valley, [6], [7] and by the Dutch high-tech industry sectors Philips Components/ NXP and ASML, imec (a Belgian research centre for micro and nanotechnology), various university research institutes and four university(s) and graduate schools (Eindhoven University of Technology and Technical Medical University Enschede on the Dutch side, KU Leuven and VUB in Flanders) to strengthen the national capabilities for semiconductor research and the supply of qualified semiconductor PhDs, as an indirect spin-off of mutual collaborations in several international research programs. Such university–industry collaborations to build-up human resources can shorten the learning curve from the university to practice and improve the relevance of curricula to industry's needs, [8].

In order to develop semiconductor industry in Vietnam, Decision No. 1018/QĐ-TTg (21/09/2024) promulgating "Strategy for Development of the Semiconductor Industry to 2030, Vision to 2050" has linked semiconductor industry development with human resource development, institutional improvement and technology - environment support infrastructure development [9]. The strategy requires immediate actions of ministries, sectors and training institutions to design, implement and coordinate with enterprises to seek resources to invest practice facilities and other learning environment of high technology semiconductor, [9], [10]. However, there is a huge gap between policy objectives and implementation capability at institutions, [3], [11].

There are basic problems in university–industry collaboration and technical education for semiconductors in Vietnam. One issue appears repeatedly when looking at current university–industry collaboration. It is not always formalized, and in many cases it takes the form of short-term internships or small sponsorship arrangements rather than structured training systems. Another point relates to how technical education is structured within universities, where a unified competency framework for the semiconductor field is still not clearly defined. Thirdly, the practical physical infrastructure, such as shared or dedicated cleanrooms and basic measurement tools and equipment (including microscopes, electron microscopes, ellipsometers, spectrophotometers, SEM, focused ion beam, TEM, X-ray diffractometers, 3D ADP, and STEM) is severely constrained to meet the semiconductor industry needs, [11], [12]. Fourthly, the mechanisms and methods for distributing responsibilities and benefits between universities and enterprises in collaborative pedagogical practices are ambiguous and thus do not motivate more active participation by enterprises. Taken together, these observations point toward the need for a more specific form of cooperation model, although what such a model should look like is not entirely settled.

Systematic review evidence suggests that academic engagement – i.e. the degree of knowledge interaction between academics and external parties – can enhance knowledge transfer and lead to practical outcomes. Notably, enterprise involvement in academic programs can facilitate curriculum design and training, and improve graduate employment through academic-industry collaboration. A number of reports and policy mappings on training programs in the US have found short-term practice, apprenticeships and scholarship/trainee programs to be major factors in alleviating labor shortages in the semiconductor industry, [2], [4], [5]. This is also a theme of recent research reported in the journals published by WSEAS in the field of engineering education and technological innovation. Structural engagement (i.e. engagement in substantive change to the curriculum or program) rather than increased intensity of links between institutions is identified as critical for effective training in high-tech fields, [13].
This research study is timely for a number of reasons. From a practical and policy perspective, there is a growing need for a university–enterprise–government collaborative model for semiconductor-related educational programs and internships that incorporates relevant technical and safety practices in Vietnam. In addition, the study reveals a need to investigate the mediational effect of the technology–adaptive curriculum on the relationship between training program inputs and practical training effectiveness (hereafter referred to as PT Efficacy). Most importantly, this study foregrounds the need for viable policy recommendations, executable cooperation schemes, and relevant competency standards that address the Country's strategic objectives towards sustainable development, [1], [9], [10], [14].

The analysis in this study is organized in several steps, beginning with model development, followed by empirical testing, and then moving toward interpretation of the results in relation to the Vietnamese context.

2 Theoretical Foundation

2.1 Triple Helix Theory

The way these activities unfold is not uniform. Some parts move faster, others more slowly, and the degree of involvement differs depending on the context rather than following a single pattern. That framing is familiar. But when looking more closely, the way these interactions actually take place does not always follow a clear or stable pattern.

The three actors are often described with distinct roles. Universities generate knowledge, enterprises apply it, and government provides direction or support. In practice, this separation is not always maintained. Universities sometimes move closer to application. Enterprises may take part in training. Not consistently. And not always in a formal way. The boundaries exist, but they shift.

This becomes easier to notice in sectors such as semiconductors. Development rarely occurs within a single institutional space. It tends to involve multiple actors at once, even when coordination is only partial. Or uneven.

There are already a number of policy documents that point in this direction, including strategies extending toward 2030 [9] and initiatives aimed at building an ecosystem in the 2025–2030 period. The orientation is there.

The way these activities unfold is not uniform. Some parts move faster, others more slowly, and the degree of involvement differs depending on the context rather than following a single pattern. Some forms of collaboration appear through specific programs or projects. In other situations, interaction remains limited, tied to certain functions rather than extending further.

Looking at these relationships through the Triple Helix perspective makes it possible to move away from formal descriptions and focus more on how things actually operate. In the Vietnamese context, the level of linkage is not uniform. Some institutions show closer coordination. Others less so. It depends.

This also helps explain why coordination mechanisms – often associated with the role of the State – are still under discussion, rather than fully in place.

2.2 Core Competence Theory

Core Competence Theory [15] is often introduced as a way to explain how organizations achieve long-term competitive advantage through distinctive capabilities. That is the standard explanation. But when trying to apply this idea to semiconductor training, things become less clear.

For universities, defining what counts as a "core" competence is not always straightforward. Teaching and research are obvious, but beyond that, there is increasing pressure to engage with emerging technologies. These technologies change quickly. Sometimes faster than universities can adapt. So what is considered "core" today may not remain so for long.

For enterprises, the situation looks more concrete, but only to a certain extent. Skills such as integrated circuit design, photolithography, chip testing, or system integration are often mentioned as key competencies. These are widely recognized. Still, their importance can shift depending on technological trends or market demand, so even here the idea of stability is somewhat relative.

There is also the issue of translation. Industry requirements are expected to guide curriculum design. In theory, this makes sense. In practice, the process is not always smooth. There can be delays. Or mismatches. Sometimes both.

In Vietnam, the limitations become more visible. Most universities do not have sufficient resources to cover the full semiconductor value chain, [3], [11], [12]. Work in this context often narrows down to a few domains where resources and experience have already accumulated, rather than being spread evenly across all areas.

That said, this also brings up another issue. Students trained in this way may enter the labor market more easily, but how long their competencies remain relevant is less clear, since it depends on how those skills continue to develop, which is not always predictable.

2.3 Fit Model Theory

Fit Model Theory is commonly used to examine how different elements within a system align with each other. The concept itself is relatively simple. Alignment is expected to improve performance. But in practice, "alignment" is not always easy to define. Or measure.

In this study, the model is used to look at three components: university training objectives, enterprise workforce demands, and State policy orientations. These elements are often discussed separately. Here they are considered together, although not necessarily in a perfectly aligned way.

When alignment is strong, collaboration tends to work better. Training outcomes improve. Enterprises face fewer difficulties in recruitment. Public investment may also become more efficient. That is the general expectation.

When alignment is weak, different types of problems begin to appear. Universities may provide training that is not closely connected to practice. Enterprises may struggle to find suitable workers. Policies do not always lead to the outcomes they are supposed to achieve. Or at least, not in a consistent way. In some cases, the effects appear delayed; in others, they are difficult to observe at all.

These issues do not necessarily occur at the same time. But they seem to be connected, in one way or another, even if the connection is not always clear. Using this model makes it possible to move away from looking at factors one by one. It shifts the focus, a bit, toward how different elements relate to each other within a broader structure.

That said, this interaction is not stable. It changes. Sometimes across contexts, sometimes even within the same setting.

Applying this model allows the study to move beyond looking at individual factors. Instead, it focuses on how different elements interact within a broader structure.

However, this interaction is not always consistent. It can vary across contexts, across institutions, and sometimes even within the same system.

So instead of trying to point to one dominant factor, the analysis here moves in a slightly different direction. It looks more at how these elements come together, or sometimes do not quite come together, in shaping collaboration in semiconductor human resource training.

In some cases, the fit seems to work reasonably well. In others, it does not. And the difference is not always easy to explain.

3 Research Methodology

3.1 Conceptual Framework

This study is developed by drawing on three theoretical perspectives, namely the Triple Helix, Core Competence Theory, and Fit Model Theory, although in practice these frameworks are not always applied as clearly separated components but tend to overlap when used to interpret how training systems function within the semiconductor industry.

The interaction among universities, enterprises, and the State is often described within the Triple Helix framework [16], [17], particularly in relation to knowledge transfer and innovation processes, where the participation of all three actors is generally considered necessary, even though the way this interaction takes place may vary depending on policy conditions and institutional arrangements, and does not always follow a consistent pattern across contexts. At the same time, the question of what training should focus on is often linked to the idea of core competencies [15], although in the semiconductor field these competencies tend to extend across multiple areas, including design, operation, and maintenance of production systems, as well as data-related capabilities and the application of advanced technologies, which are sometimes treated as distinct categories but in practice are often interconnected.

This also relates to how different elements within the system align with one another, which is the main concern of Fit Model Theory [18], where effectiveness is associated with the degree of compatibility among components, although in real settings this alignment is rarely complete, and in some cases partial misalignment may still persist without immediately affecting observable outcomes, at least in the short term.Accordingly, these three theoretical frameworks complement one another in shaping the structure of the research model: the Triple Helix defines the collaboration mechanism, Core Competence clarifies the focus of training, and the Fit Model ensures logical coherence and alignment among the elements.

Based on this foundation, the study identifies a system of factors (Figure 1, Appendix).

(1) Industry Engagement: This factor reflects the level of enterprise commitment and presence in curriculum design, teaching, internship support, and technology transfer. International research has demonstrated that substantive enterprise participation enhances practical relevance and improves students' professional competence, [19], [20], [21].

(2) Program Quality: This factor captures the comprehensiveness, currency, and responsiveness of the training program. A program with a well-structured curriculum, modern pedagogical approaches, and content aligned with international standards provides a crucial foundation for enhancing the quality of semiconductor human resources. Program quality is widely recognized as a decisive factor in the development of students' professional competencies, [22].

(3) Technology Practice: This factor emphasizes the integration of advanced technologies into teaching and practice. It includes the use of simulation software, CAD/EDA systems, as well as pilot production equipment. In the context of rapid technological change in the semiconductor industry, the capacity to integrate technology into training becomes a key determinant enabling students to access real industrial environments, [1], [2], [5], [7], [12].

(4) Skill & Career Development: This factor represents the role of training programs and enterprise collaboration in providing opportunities for soft skill development, project management skills, and post-graduation career orientation. Alignment between training competencies and labor market expectations significantly increases graduate employability, [23].

(5) Technology–Adaptive Curriculum (mediating variable): This factor reflects the flexibility and adaptability of the training program in updating emerging technologies. Beyond maintaining content quality, it concerns the capacity to restructure curricula to respond to advancements in semiconductor manufacturing and design. It functions as the bridge that transforms input factors (industry engagement, program quality, technology practice, skill & career development) into actual training outcomes, [7], [16], [17], [19], [24].

(6) State Role (moderating variable): In the Vietnamese context, the State plays an important role in formulating preferential policies, issuing supportive regulations, and investing in infrastructure for the semiconductor sector. According to the Triple Helix framework, the State acts not only as a "referee" but also as an active "player". Appropriate institutional intervention can either reinforce or constrain collaborative effectiveness depending on implementation context, [25].

(7) Practical Training Effectiveness (dependent variable): This is the ultimate outcome of the model, reflecting students' practical competence, problem-solving capability in real contexts, and readiness to enter the labor market. Measuring practical training effectiveness is essential for evaluating the quality of university–industry collaboration systems, [21].

Based on the theoretical foundations of the Triple Helix [16], [17], Core Competence [15], [26], and Constructive Alignment [27], this study proposes that coordination among actors within the education–industry–State ecosystem may influence the effectiveness of semiconductor workforce training. Furthermore, mediating and moderating factors may alter both the magnitude and direction of these relationships. Accordingly, the following research hypotheses are formulated:

(1) H1+. Industry engagement, program quality, and learner skill capacity have positive relationships with practical training effectiveness.
(2) H2+. The technology–adaptive curriculum mediates the relationship between input factors (industry engagement, program quality, skill development) and practical training effectiveness.
(3) H3+. The moderating role of the State influences the relationship between training programs and output effectiveness, such that different levels of intervention produce differences in training outcomes. *different training outcomes.*

3.2 Research Design

This study adopts a quantitative approach with a cross-sectional survey design to analyze the impact of factors identified in the theoretical framework (Triple Helix, Core Competence Theory, Fit Model Theory) on practical training effectiveness in the semiconductor technology sector. A controlled convenience sampling method was applied to ensure feasibility in accessing respondents while maintaining diversity and balance across demographic and professional characteristics.

Data for the study were collected using a questionnaire designed around the main constructs of the research model. The items were not created entirely from scratch but were adapted from established studies and subsequently contextualized for semiconductor workforce training, [15], [16], [17], [18], [19], [26].

A five-point response scale was used so that participants could express different levels of agreement, [28], [29]. Through this, the survey captured how respondents viewed issues such as the extent of industry involvement, the quality of training programs, the use of technology in learning, the development of skills, and the extent to which the curriculum adapts to technological change, along with perceptions related to policy and training outcomes.

Participants came from three main backgrounds. One group consisted of students studying in fields closely related to semiconductor training, including information technology and engineering disciplines. Another group included lecturers and staff involved in teaching or curriculum-related work. The remaining participants were drawn from enterprises and research-related organizations that had some form of involvement in training or student support activities.

After screening, 265 responses were retained for analysis (Table 1, Appendix). The data were then organized by several background characteristics, which makes it possible to compare how different groups view the same issues, even though these views do not always align, [30].

Ethical considerations were taken into account throughout the process, [29], [31]. Participants were informed about the study before completing the questionnaire, and no identifying information was recorded. Participation was voluntary, and respondents could choose to stop at any time. The study followed general ethical guidelines as well as national regulations in Vietnam, [29].

3.3 Scale Structure and Reliability

First, descriptive statistics of the data collection instrument (Table 2, Appendix) indicate that the research scale comprises six factors, including four independent variables (Industry Engagement – IV_IE, Program Quality – IV_PQ, Technology Practice – IV_TP, Skill & Career Development – IV_SC), one mediating variable (Technology–Adaptive Curriculum – MV_TC), and one dependent variable (Practical Training Effectiveness – DV_PT). A total of 53 observed variables were designed to comprehensively reflect theoretical dimensions and ensure the capacity to test relationships within the model.

Internal reliability assessment results (Table 3, Appendix) show that all scales achieved high Cronbach's Alpha coefficients, ranging from 0.883 to 0.959, far exceeding the minimum threshold of 0.7, [32]. This indicates high internal consistency among items within each factor. Reliability levels remain high across the constructs, ranging from about 0.88 for technology practice to just over 0.91 for industry engagement, while the mediating variable is close to 0.91 and the dependent variable reaches nearly 0.96.

All item–total correlations are above 0.5, indicating that the observed variables are consistently aligned with their respective constructs and no items require removal, [32].

For the full sample (N = 265), the CFA results show a very good overall fit of the measurement model, with indices such as CMIN/DF close to 1.0, TLI and CFI both near 1, and RMSEA remaining well below 0.05, alongside a PCLOSE value reaching 1.000 (Table 4, Appendix). This combination of fit indices supports the conclusion of strong model adequacy, [33].

The non-significant chi-square result supports acceptable covariance-model fit under SEM assumptions, [34], [35].

Modification indices fall within a relatively narrow range (about 4.06 to 9.96), with no unusual values, so the model appears stable before proceeding to multi-group analysis.

The initial sample comprised three groups: Students (n = 144), Lecturers/Researchers (n = 79), and Enterprise Representatives/Managers (n = 42). To ensure the stability of Maximum Likelihood estimation in MG-SEM and meet minimum sample size requirements for each group [36], the two professional groups were combined into "Professional Stakeholder" (n = 121).

The grouping decision is theoretically grounded: both represent professional actors within the training–research–transfer collaboration ecosystem, sharing strategic roles and similar professional experience, and differing fundamentally from students. Thus, the revised grouping structure reflects role-based differentiation consistent with both theoretical and methodological considerations.

Following common procedures [30], [31], [37], measurement invariance was examined in a stepwise manner within the CB-SEM framework using ML estimation (Table 4, Appendix).

(1) Configural invariance. CFI = 0.933, TLI = 0.929, RMSEA = 0.024, CMIN/DF = 1.153. Same factor pattern in both groups.

(2) Metric invariance. CFI: 0.933 → 0.932. No material change across groups.

(3) Scalar invariance. When intercepts are also fixed, CFI drops further to 0.887 (ΔCFI = 0.045), while RMSEA remains at 0.031.

The decrease is more noticeable here, although the model itself does not break down, and it can still be used, but comparisons across groups should probably be treated with some caution, [37].

Because the research objective focuses on comparing structural relationships across role groups rather than latent mean differences, metric invariance is both necessary and sufficient, [38]. Accordingly, the model satisfies methodological requirements for implementing MG-SEM based on Maximum Likelihood estimation in the subsequent stage.

4 Research Results

4.1 Testing Structural Effects within the Structural Equation Model

The structural model was estimated after confirming the measurement model. The estimation relied on the Maximum Likelihood (ML) method within a Covariance-Based Structural Equation Modeling (CB-SEM) framework, which is a fairly common approach in this type of analysis. ML was selected mainly because it tends to perform well under moderate sample sizes and when the data distribution is not too far from normality, although in practice these assumptions are not always perfectly satisfied, [35], [36], [39].

To examine the stability of the estimates, especially for indirect and interaction effects, a Bootstrap procedure with 5,000 resamples was conducted, [40], [41], [42]. This step was included to obtain 95% confidence intervals for the path coefficients. The intention here is quite straightforward: traditional normal-theory tests may not always capture the complexity of mediation or moderation, particularly in structural models that are not strictly linear. Bootstrap is often used in such situations, even though it does not completely eliminate all sources of uncertainty, [41], [43].

Looking at the model fit, the χ^2/df ratio is 1.627, which falls below the commonly cited threshold of 3.0 (Table 5, Appendix). This suggests that the discrepancy between the observed covariance matrix and the model is not large. At least not excessively large.

The RMSEA value is 0.049, which is slightly below the 0.05 threshold. This is generally interpreted as a good fit, although the distinction between "good" and "very good" is sometimes less clear in applied studies, [33].

The incremental fit indices, however, are somewhat lower than expected. CFI is 0.856 and TLI is 0.851 (Table 5, Appendix), both below the conventional 0.90 benchmark. This would normally raise concerns if the model were purely a measurement model. In this case, the model includes multiple structural paths and interaction terms, which tend to reduce these indices. This effect has been noted in previous work [44], although the extent to which it should be accepted is still debated.

Given this, the combination of χ^2/df below 2 and RMSEA below 0.05 is considered sufficient for proceeding with interpretation, even if not all fit indicators are ideal. This is not uncommon in more complex structural models, [35].

The results indicate that all four input variables – Industry Engagement, Program Quality, Skill and Career Development, and Technology Practice – have positive and statistically significant effects on the Technology–Adaptive Curriculum (MV_TC), with p-values below 0.001. This suggests that curriculum adaptability is not driven by a single factor, but rather by a combination of inputs that accumulate over time.

The path from MV_TC to Practical Training Effectiveness (DV_PT) is particularly strong ($\beta = 0.973$, $p < 0.001$). This is a large coefficient. Possibly very large. It indicates that the mediating variable plays a central role in the model, essentially acting as the main channel through which input factors influence outcomes.

This interpretation is broadly consistent with the logic of the Triple Helix framework [17] and Core Competence theory [15], where interaction and capability development are not direct, but occur through intermediate mechanisms. In this case, that mechanism appears to be the technological adaptability of the curriculum.

The role of the State is less clear. The direct effect (State → DV_PT) does not reach statistical significance at the 5% level ($p = 0.096$). This suggests that institutional influence may not operate as an independent determinant, at least not in a direct way. Or not in a way that is easily captured by this model.

The interaction term (MV_State) shows a negative and statistically significant coefficient ($\beta = -0.155$, $p < 0.001$). At first glance, this seems meaningful. However, significance alone is not sufficient. The stability of this effect needs to be examined more carefully.

When looking at the Bootstrap confidence intervals, the results are less straightforward. The interval for the MV_TC → DV_PT path does not include zero, which supports the mediating role of MV_TC. The indirect effects of IV_IE, IV_PQ, and IV_TP also remain positive, reinforcing the idea of an indirect transmission mechanism (Table 6, Appendix).

In contrast, the confidence interval for the interaction term (MV_State → DV_PT) includes zero ([-0.634; 0.053]). This is important. It suggests that the moderating effect is not stable under resampling. Confidence intervals including zero indicate insufficient evidence for robust effect generalization, [43], [45], [46].

This creates a small inconsistency. The coefficient is significant under ML estimation, but not supported by Bootstrap. This does not necessarily invalidate the result, but it does make it less certain.

Overall, the model appears to operate primarily through a mediating mechanism. Input factors influence training effectiveness indirectly, through the technological adaptability of the curriculum, rather than through direct intervention from the State. This pattern is relatively clear in the estimates, even if some relationships remain less stable than others. The causal structure can be expressed in the following system of equations:

$$MV\_TC = 0.481*IV\_IE + 0.658*IV\_PQ + 0.530*IV\_SC + 1.015*IV\_TP + \zeta_1$$

$$DV\_PT = 0.973*MV\_TC + 0.054*State - 0.155*(MV\_TC*State) + \zeta_2$$

given that $\beta_1 \gg \beta_2$ and that β_2 is unstable under Bootstrap estimation, the empirical data support the mechanism:

(IV_IE; IV_PQ; IV_SC; IV_TP) → MV_TC → DV_PT

rather than a model in which: *State → DV_PT*

This implies that practical training effectiveness is primarily determined by the program's technological adaptability, whereas the role of institutional context operates as a conditional factor rather than a direct causal driver.

4.2 Multi-Group Structural Analysis by Actor Role

Previous Bootstrap results indicated that the moderating effect of the interaction term MV_State (MV_TC × State) is unstable (95% confidence interval includes zero). According to structural modeling principles, multi-group comparisons should be conducted only on a baseline model empirically supported at the aggregate level, [35], [36]. Therefore, Multi-Group SEM (MG-SEM) was implemented using a reduced model excluding the interaction term to assess the stability of core structural relationships across actor roles.

The analysis was conducted on the two theoretically justified groups defined earlier: Students (n = 144) and Professional Stakeholders (n = 121), comprising lecturers/researchers and enterprise representatives. The consolidation of professional groups ensures sufficient sample size for stable ML estimation while reflecting role-based stratification within the semiconductor training collaboration ecosystem.

MG-SEM followed the standard two-step procedure, [6]. First, the unconstrained model allowed structural coefficients to vary freely across groups. Second, the constrained model imposed equality constraints on the principal structural paths (IV → MV_TC; MV_TC → DV_PT; State → DV_PT) across the two groups. Model differences were evaluated using ΔCFI.

|ΔCFI| is 0.001. The value stays very close to zero. CMIN/DF remains below 2, and RMSEA is 0.036. No noticeable change across the specifications (Table 7, Appendix). The model behaves in a similar way after the constraints are applied.In other words, there is no empirical evidence suggesting that causal relationships differ between the Student and Professional Stakeholder groups. The structural mechanism of the model remains consistent across actor roles.

The result |ΔCFI| = 0.001 implies no meaningful difference between the two specifications, that is:

$$\gamma_i^{(S)} \approx \gamma_i^{(P)}; \beta_i^{(S)} \approx \beta_i^{(P)}$$

This suggests that the underlying causal structure of the training collaboration system does not depend on actor role but operates through the same mechanism across students and professional actors.

Methodologically, MG-SEM results reinforce the structural stability of the model and confirm that group comparisons are valid based on previously established measurement invariance, [30]. Theoretically, this finding underscores the central and universal role of curriculum technological adaptability within the semiconductor collaboration ecosystem, irrespective of participant role.

This structural consistency clarifies that any differences between groups – if present – lie in perception levels or evaluative intensity rather than in the fundamental nature of the causal mechanism.

5 Findings and Discussion

5.1 Key Findings

This study yields three theoretically significant findings regarding the university–industry–State collaboration model in semiconductor workforce training in Vietnam.

(1) Endogenous mediation constitutes the core operating axis of the system

The most prominent finding is the central and stable role of the Technology–Adaptive Curriculum in transmitting the effects of input factors (Industry Engagement, Program Quality, Technology Practice, Skill & Career Development) to Practical Training Effectiveness. The large and consistent structural coefficient of the MV_TC → DV_PT path, together with robust indirect effects confirmed through Bootstrap, indicates that training effectiveness is not the direct outcome of isolated factors but rather the product of an endogenous adjustment mechanism embedded within the training program.

This finding refines and concretizes Core Competence theory [15]: the core capability of the training system does not lie in the mere degree of enterprise participation or fragmented technological investment, but in the program's capacity to restructure itself in order to integrate, update, and synchronize technological knowledge. In other words, adaptability itself becomes the "core competence of competencies."

From the perspective of Fit Model theory [18], empirical results suggest that alignment between inputs and outputs does not occur directly but is mediated through a coordinating structure – namely, MV_TC. This implies that systemic fit is dynamic rather than a static compatibility among components.

(2) The moderating role of the State does not operate in a linear manner

The findings do not provide stable support for the moderating role of the State. Although the interaction coefficient is significant under ML estimation, Bootstrap testing indicates insufficient evidence to confirm a stable moderating effect.

This result does not negate the State's role within the Triple Helix ecosystem [17], but suggests a more nuanced interpretation: the State does not directly influence training effectiveness at the micro-level of program operation, nor does it consistently alter the strength of technological adaptability effects. Instead, its role may operate at a broader institutional layer – establishing foundational conditions, policy frameworks, and infrastructure – rather than intervening directly in the internal operational mechanism of training programs.

From a theoretical standpoint, this finding raises an important question for the interpretation of the Triple Helix in transitional economies: does stronger institutional intervention always enhance collaborative effectiveness, or is optimal performance achieved only when endogenous mechanisms reach sufficient maturity? In the case of Vietnam's semiconductor sector, the data suggest that decisive influence lies in curriculum adaptability rather than in the intensity of policy regulation.

(3) Causal structure remains stable across actor roles

MG-SEM results indicate no significant differences in structural coefficients between the Student and Professional Stakeholder groups. This implies that the operating mechanism of the model is role-invariant, despite potential differences in evaluative intensity or perception.

Theoretically, this carries two implications. First, it reinforces the Triple Helix assumption that actors within the ecosystem share a foundational interaction structure, despite differences in interests and positional status. Second, it suggests that the mechanism generating training effectiveness in high-technology sectors does not depend on the subjective characteristics of participating groups but on the structural logic of the training system.

This structural stability clarifies that differences – if any – exist at the perceptual or evaluative level rather than at the level of causal structure. It helps distinguish between two analytical levels often conflated in education–industry collaboration research: perceptual differences versus structural differences.

Repositioning the collaboration model in high-technology contexts

Taken together, these findings indicate that effective collaboration in semiconductor workforce training is neither a model of intensified regulation nor one of expanded participation, but rather a model centered on optimizing curriculum adaptability under conditions of rapid technological change.

Accordingly, the theoretical contribution of this study lies not merely in testing a specific model in Vietnam, but in proposing a structural reinterpretation:

In high-technology sectors characterized by rapid innovation cycles, the adaptive mediating mechanism occupies the central position within the collaborative ecosystem, while institutional factors operate as background conditions rather than direct moderating drivers.

This insight extends the interpretation of the Triple Helix framework in developing economies, where the balance between institutional coordination and program autonomy is decisive for the effectiveness of strategic workforce training.

5.2 Conclusion

If Section 5.1 focuses on specific empirical findings, this conclusion addresses a broader question: *how should the collaboration model for semiconductor workforce training be reinterpreted in light of the empirical evidence?*

First, the study demonstrates that effectiveness within high-technology collaboration ecosystems does not operate according to a linear additive logic among actors (State – University – Enterprise), but according to a logic of structural mediation. Training effectiveness does not increase simply as linkage intensity rises; rather, it improves when training programs possess sufficient self-adjustment capacity to absorb, integrate, and transform technological signals from the external environment. This reorients the theoretical focus of the Triple Helix: instead of concentrating on the geometry of relationships among three actors, attention should shift toward the endogenous coordinating capacity of the training system.

Second, the absence of stable evidence for a direct moderating role of the State should not be interpreted as institutional weakness, but as an indication of stratified impact. Empirical results suggest that institutions operate at the macro-structural level, establishing boundary conditions for adaptation, without directly intervening in the micro-equation of training effectiveness. In high-technology environments characterized by rapid innovation cycles, effective governance lies not in the degree of intervention, but in the capacity to create space for endogenous adaptation. This constitutes an important adjustment in interpreting the Triple Helix within transitional economies.

Third, structural invariance across role groups indicates that the causal model is systemic and not dependent on actor position. This carries methodological significance: differences between groups – if present – pertain to evaluative intensity or perception rather than to operational structure. Distinguishing these levels prevents the common conflation of perceptual variation with structural variation and strengthens the robustness of the model at the structural level.

At the scholarly level, the study contributes in three ways. First, it provides empirical evidence for the central role of curriculum adaptability as a mediating mechanism in high-technology sectors – a variable rarely operationalized with clarity in prior research. Second, it refines the understanding of institutional regulation within the Triple Helix, shifting from assumptions of direct moderation to a background-condition perspective. Third, it integrates CB-SEM, Bootstrap, and MG-SEM within a unified design, ensuring rigor in structural inference and group comparison.

Overall, this study proposes a different perspective on collaboration in semiconductor workforce training: effectiveness derives not from increasing actor presence, but from constructing a sufficiently adaptive structural configuration capable of absorbing technological volatility. In the context of digital transformation and global technological competition, this may represent a prerequisite condition for emerging economies to develop strategic human capital sustainably.

6 Managerial Implications

Four points can be noted from the model, though not all of them are equally clear.

(1) At the program level, adding more connections does not seem to change much on its own. What appears more relevant is how programs deal with technological updates. In some cases, this comes down to how often content is revised, or how learning outcomes are adjusted. Not always systematic.

(2) Collaboration is present, but often in a limited form. Internships, short-term involvement. When it moves into co-design or shared development of modules, the situation looks different, although this is not always observed across cases, [47].

(3) At the institutional level, structures do not always follow the same logic as the system itself. Some processes require faster feedback, but administrative arrangements are not always built for that. The mismatch is there, though not always visible.

(4) At the policy level, direct intervention does not consistently show clear effects. In several cases, what seems to matter more are background conditions—flexibility, infrastructure, funding. Changes tend to happen from within rather than from external control.

Overall, the issue does not appear to be about scale or intensity, but about how the system adjusts internally. This is not entirely straightforward.

6.1 Research Limitations

The data used here are taken at a single point in time and come from self-reports, so what is being captured is more of a snapshot than a process. Changes that might unfold gradually – especially those related to technological adaptation – are therefore not really visible in this design. One possible extension would be to follow the same relationships over time, or to look at them across different layers of the system, where approaches such as longitudinal data, dynamic SEM, or multilevel analysis may become more relevant. These directions are not explored here. There is also the question of how far perception-based measures can represent actual outcomes. Bringing in more objective indicators – such as technological outputs or labor performance – could make the picture more grounded, although this would require a different type of data collection.

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The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

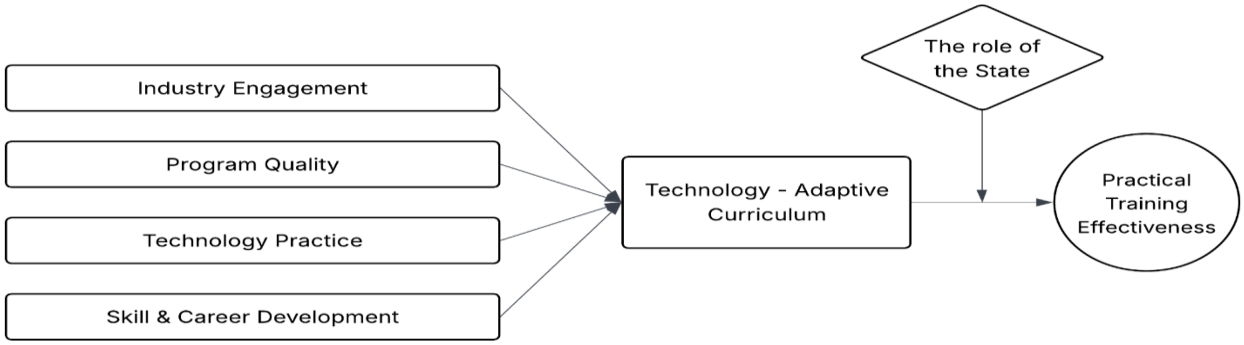

Fig. 1: Research Model of the Study

Source: Create by Authors

Table 1. Descriptive Statistics of the Research Sample

Gender	Male	238 (89.81%)
	Female	27 (10.19%)
Age	Under 22	48 (18.11%)
	22-25	67 (25.28%)
	26-30	52 (19.62%)
	Over 30	98 (36.98%)
Role	Student	144 (54.34%)
	Faculty/Researcher	79 (29.81%)
	Industry Expert/Manager	42 (15.85%)
Education level	College	53 (20.00%)
	Bachelor's	88 (33.21%)
	Master's	72 (27.17%)
	Doctorate	43 (16.23%)
	Postdoctoral	9 (03.40%)
Institution type	University/Research Institute	198 (74.72%)
	Industry	47 (17.74%)
	Government/Regulatory Agency	20 (07.55%)
Experience	<1 year	45 (16.98%)
	1-3 years	62 (23.40%)
	3-5 years	73 (27.55%)
	>5 years	85 (32.08%)

Source: IBM SPSS Statistics 27.0

Table 2. Description of Data Collection Tools

	Factor	*Encryption*	*N**
Independent Variables			
1	Industry Engagement	IV_IE	10
2	Program Quality	IV_PQ	10
3	Technology Practice	IV_TP	8
4	Skill & Career Development	IV_SC	9
Mediating Variable			
5	Technology – Adaptive Curriculum	MV_TC	8
Dependent Variable			
6	Practical Training Effectiveness	DV_PT	8
N - Number of Observed Variables*			

Source: Create by Authors

Table 3. Internal Consistency Reliability Results

Construct	*Corrected Item–Total Correlation*	*Cronbach's Alpha if Item Deleted*	*Cronbach's Alpha*
Independent Variables			
IV_IE	0.620 – 0.761	0.900 – 0.908	0.913
IV_PQ	0.595 – 0.754	0.891 – 0.901	0.906
IV_TP	0.550 – 0.728	0.860 – 0.878	0.883
IV_SC	0.580 – 0.717	0.878 – 0.889	0.895
Mediating Variable			
MV_TC	0.660 – 0.743	0.890 – 0.898	0.906
Dependent Variable			
DV_PT	0.805 – 0.882	0.950 – 0.955	0.959

Source: IBM SPSS Statistics 27.0

Table 4. Result of the Model Fit Analysis (CFA)

Indicator	*Value*	*Multi Group*		
		Configural Invariance	*Metric Invariance*	*Scalar Invariance*
CMIN	1335.644	3015.366	3066.976	3383.299
DF	1309	2616	2663	2716
P	0.298	0.000	0.000	0.000
CMIN/DF	1.020	1.153	1.152	1.246
GFI	0.847	0.732	______	______
TLI	0.996	0.929	0.929	0.886
CFI	0.997	0.933	0.932	0.887
RMSEA	0.009	0.024	0.024	0.031
PCLOSE	1.000	1.000	1.000	1.000
M.I – Covariances	4.060 – 9.962	4.004 – 10.610	4.007 – 11.324	4.031 – 11.061
|ΔCFI|			0.001	0.045

Source: IBM Amos Statistics 24.0

Table 5. Results of Structural Model Fit Analysis

Indicator	*Value*
CMIN	3679.623
DF	2262
P	0.000
CMIN/DF	1.627
TLI	0.851
CFI	0.856
RMSEA	0.049

Source: IBM Amos Statistics 24.0

Table 6. Bootstrap 95% Confidence Intervals of Direct and Indirect Effects

Effect		*95% CI*	
		Lower	*Upper*
IV_IE → MV_TC		0.037	1.115
IV_PQ → MV_TC		0.145	1.222
IV_SC → MV_TC		-0.104	1.112
IV_TP → MV_TC		0.359	1.364
MV_TC → DV_PT		0.750	1.034
MV_State → DV_PT		-0.634	0.053
Indirect MV_TC → DV_PT	IV_IE	0.046	1.181
	IV_PQ	0.187	1.243
	IV_SC	-0.057	1.114
	IV_TP	0.364	1.363

Source: IBM Amos Statistics 24.0

Table 7. Results of Structural Invariance Test Between the Two Role Group

Indicator	*Value*	
	Unconstrained	*Constrained*
CMIN	4725.562	4723.527
DF	3510	3516
P	0.000	0.000
CMIN/DF	1.346	1.343
TLI	0.834	0.835
CFI	0.841	0.842
RMSEA	0.036	0.036
|ΔCFI|		0.001

Source: IBM Amos Statistics 24.0