A Comparative Efficiency Assessment of Short-term Skill Training Providers using Data Envelopment Analysis

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ABSTRACT

India's short-term skill training (STT) programs have emerged as a strategic response to the country's pressing employability challenges, particularly among its vast and diverse youth population. Despite significant public investment and policy attention, the performance of Training Providers (TPs) under government-sponsored schemes remains uneven, raising critical questions about operational efficiency, equity, and long-term impact. This doctoral research undertakes a comprehensive efficiency assessment of 134 TPs operating in West Bengal, aiming to identify the structural, contextual, and managerial factors that distinguish high-performing institutions from those lagging behind.

The study adopts a mixed-methods design, integrating quantitative benchmarking through an output-oriented Variable Returns to Scale (VRS) Data Envelopment Analysis (DEA) model with qualitative insights drawn from training providers and certified trainees. DEA inputs include the number of enrolled trainees, average trainer experience, and average course duration, while the output is defined as the number of certified trainees. To account for heterogeneity among providers, K-means clustering is employed to group TPs into operationally similar categories, enabling both cluster-wise and global efficiency analysis. A second-stage Tobit regression is used to examine the influence of contextual variables—such as gender and social inclusion—on efficiency scores. The qualitative strand complements this analysis through thematic exploration of stakeholder feedback, offering interpretive depth and grounding the findings in real-world operational dynamics.

Key findings reveal that only 18% of TPs are fully efficient, with Industry-Integrated models consistently outperforming Center-Based ones across clusters. Female trainee participation emerges as a statistically significant positive factor, suggesting that gender-inclusive practices may enhance institutional performance. Many Center-Based TPs exhibit signs of scale inefficiency, indicating that mismatches in operational scale—rather than purely technical limitations—often drive underperformance. Qualitative insights underscore the importance of employer engagement, adaptive curriculum design, structured counselling, and robust feedback mechanisms as hallmarks of high-performing providers. Conversely, challenges such as equipment shortages, weak placement linkages, and limited community outreach are prevalent among less efficient institutions.

The study concludes with a set of actionable recommendations for policymakers, administrators, and implementing partners. These include the institutionalization of peer-learning frameworks, gender-inclusive operational incentives, process-linked funding conditions, and targeted capacity-building initiatives to optimize scale and improve delivery quality. While the findings are specific to West Bengal's government-sponsored schemes, the methodological framework offers transferability to other states and sectors. By combining rigorous quantitative analysis with grounded qualitative insights, this research contributes both a policy playbook for enhancing TP efficiency and a replicable model for future assessments within India's evolving skill development ecosystem.

Keywords: Data Envelopment Analysis, skill development, training providers, technical efficiency, mixed methods, technical education

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LIST OF ABBREVIATIONS

Sl.no.	Acronym	Full Form
1	CB	Center-based
2	CRS	Constant Returns to Scale
3	DDUGKY	Deen Dayal Upadhyaya Grameen Kaushalya Yojana
4	DEA	Data Envelopment Analysis
5	DMUs	Decision Making Units
6	GoWB	Government of West Bengal
7	II	Industry-Integrated
8	ILO	International Labour Organization
9	MSDE	Ministry of Skill Development and Entrepreneurship
10	NCVET	National Council for Vocational Education and Training
11	NEP	National Education Policy
12	NSDC	National Skill Development Corporation
13	NSQF	National Skill Qualification Framework
14	OECD	Organisation for Economic Co-operation and Development
15	PMKVY	Pradhan Mantri Kaushal Vikas Yojana
16	PTE	Pure Technical Efficiency
17	SSC	Sector Skill Council
18	STT	Short Term Skill Training
19	TET&SD	Technical Education, Training and Skill Development
20	TP	Training Provider
21	TVET	Technical and Vocational Education and Training
22	UNESCO	United Nations Educational, Scientific and Cultural Organization
23	VRS	Variable Returns to Scale

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

India's skill development landscape is at an inflection point. With one of the world's largest youth populations—nearly 420 million (29 percent of the total) aged 15–29 in 2024 and a rapidly evolving labour market, India faces the dual challenge of scale and relevance in workforce preparation. Short-term skill-training (STT) programs have emerged as a key response, aiming to equip youth, particularly from underserved communities, with employable skills in a short span (Price360, 2024, ILO, 2012). This shift can be understood via **Human Capital Theory** (Becker, 1964), which posits that investments in training raise individual productivity and societal wealth. STT programs thus serve as targeted human-capital investments, enhancing both private returns (higher trainee earnings) and public returns (economic growth).

Flagship national schemes such as the Pradhan Mantri Kaushal Vikas Yojana (PMKVY) and Deen Dayal Upadhyaya Grameen Kaushalya Yojana (DDUGKY); and state government schemes such as Pramod Mahajan Kaushalya Vikas Abhiyan (Maharashtra), Additional Skill Acquisition Programme (Kerala), Utkarsh Bangla (West Bengal), and so on, operationalize this vision by partnering with a wide range of Training Providers (TPs). While these schemes have expanded access and outreach, outcomes remain mixed. Placement rates, certification success, dropout levels, and cost-effectiveness vary widely across providers (Shi & Bangpan, 2022; Cho et al., 2013; Jespersen et al., 2007; Fuchs et al., 2021), raising a critical question—not just who is delivering, but how well.

Many advanced economies have developed structured skill development systems that offer useful points of comparison for India. For example, Germany's dual system blends classroom-based vocational education with industry apprenticeships, and typically evaluates efficiency through metrics such as course completion rates, job placement, and feedback from employers (Euler, 2013). In Singapore, the SkillsFuture initiative promotes lifelong learning and tight industry alignment, using indicators like wage growth, long-term employment stability, and employer satisfaction to assess training effectiveness (SkillsFuture Singapore, 2024).

While both systems report higher placement and retention outcomes, they also face their own constraints—such as limited adaptability in rapidly evolving sectors or the need for sustained industry investment. In contrast, India's short-term skill training landscape is defined by its sheer scale, regional variation, and a long-standing emphasis on output-based metrics like certification numbers and placement rates. This study situates efficiency measurement within that distinct Indian context, while also drawing on global lessons in benchmarking to explore what makes certain providers more effective than others—despite shared structural limitations.

Moreover, DEA's notion of an efficiency frontier parallels foundational organizational-efficiency frameworks (Farrell, 1957; Deming, 1986), where the frontier represents best-practice management and continuous process improvement.

Research Gap

Traditional monitoring metrics often fall short in capturing operational efficiency amid heterogeneity in provider types, geographies, and resource constraints. This creates a clear research gap in understanding performance variation in a structured, comparative, and diagnostic manner. Existing literature emphasizes enrolment and certification numbers but rarely benchmarks provider efficiency or examines underlying drivers.

As a non-parametric frontier technique, output-oriented VRS DEA enables nuanced comparisons by identifying best-performing peers and measuring the relative distance of others from the efficiency frontier (Banker, Charnes, & Cooper, 1984; Emrouznejad &

Yang, 2018). DEA is uniquely suited to contexts like Skill Development, where multiple inputs (enrolment, trainer experience, training duration) and outputs (certifications, placements) coexist, and no fixed functional relationship can be assumed. In such a resource-constrained, outcome-driven environment, efficiency is not merely a technical construct but central to achieving scale, sustainability, and social impact.

Moreover, efficiency scores alone do not explain why certain providers outperform others despite similar resources. To bridge this gap, this study adopts a mixed-methods design. While DEA quantifies relative technical efficiency, qualitative inquiry explores the organizational strategies, structural constraints, and lived experiences of providers and trainees that shape those outcomes. This combined approach strengthens explanatory power and ensures that findings are grounded in real-world operational dynamics.

By benchmarking providers, comparing performance across types (e.g., Center-Based vs. Industry-Integrated), and linking technical metrics with qualitative insights, the study aims to provide not only an assessment but also a set of actionable recommendations. These are intended for policymakers, administrators, and implementing partners looking to improve resource utilization, target setting, and accountability in India’s short-term skill training ecosystem.

In this way, the research addresses a key void in current literature—where much focus has been placed on enrolment and certification numbers, but little attention paid to the comparative efficiency of training providers or the internal and external factors that drive it.

Few studies have systematically integrated technical tools like Data Envelopment Analysis (DEA) with contextual and qualitative insights to examine not just *what* outcomes are achieved, but *how* and *why* performance varies across heterogeneous providers. This gap is especially pressing given recent policy shifts and rising public investment in skilling. By combining DEA with qualitative inquiry, this study offers a timely and innovative framework to uncover the drivers of provider efficiency and inform more evidence-based improvements in India's skill training ecosystem.

1.1.1 Understanding Skill: Definition and Scope

Before Defining what is meant by *skill* is fundamental before examining the efficiency of training providers. Internationally, skills are described as bundles of knowledge, attributes, and capacities that can be taught and enable individuals to consistently and successfully perform an activity or task (OECD, 2012). Within this broad definition, three categories are typically recognized: foundational skills such as literacy, numeracy, and digital literacy; technical skills that are specific to a job role or sector; and soft skills, which include cross-cutting attributes like communication, adaptability, and problem-solving (OECD, 2019; UNESCO). Global workforce development models stress the equal importance of all three domains. Foundational competencies provide the entry-level readiness to participate in training, technical skills ensure occupational proficiency, and soft skills allow for long-term employability and workplace integration. This framework underscores that being "skilled" is not simply a matter of acquiring technical know-how, but of developing a holistic set of capacities that allow individuals to succeed in changing labour market conditions.

In India, however, short-term skill training programs—such as the Pradhan Mantri Kaushal Vikas Yojana (PMKVY) and Deen Dayal Upadhyaya Grameen Kaushalya Yojana (DDUGKY)—have historically emphasized fast-tracking technical skills. Foundational competencies are generally treated as entry requirements rather than training priorities, while soft skills are increasingly included but not always assessed with the same rigour as technical outcomes. These programs are typically time-bound, ranging from 200 to 600 hours, and are designed to produce workforce-ready individuals in high-demand sectors such as logistics, retail, construction, apparels, textiles, and renewable energy. The focus is strongly outcome-driven: candidates are expected to transition quickly from training to employment, with technical certification acting as the primary indicator of success. This approach differs from global practice where all three skill domains are balanced, but reflects India's policy priority of rapidly expanding employability opportunities for its large youth population. Thus, within this thesis, the term *skill* refers most directly to technical and vocational competencies, complemented by embedded soft skills that enhance job readiness, while foundational skills remain outside the immediate scope of short-term training interventions.

At the same time, it is important to recognize that the value of technical and vocational skills extends beyond proficiency in a trade. In an economy where industries are evolving rapidly, employers increasingly expect candidates to adapt, apply learning in real workplace contexts, and demonstrate potential for career growth. This dynamic highlight the concept of *employability elasticity*—the idea that certain skills narrow the gap between candidate capability and job requirements, thereby improving not just initial placement but also sustained employment (Fajarsyah & Okfernando, 2025; Generalao et al., 2025; Pradhan, 2023). In this light, training providers are not only responsible for imparting sector-specific competencies but also for ensuring that trainees can transition effectively into the labour market. The efficiency of providers, therefore, lies in how well they convert inputs—such as enrolments, trainer experience, and course duration—into outputs like certification, job readiness, and eventual placement. By grounding the concept of "skill" in the operational realities of short-term, job-focused training, this study positions efficiency not just as a technical metric, but as a reflection of how effectively India's youth are being prepared for sustainable participation in the world of work.

1.1.2 Evolution of Skill Development in India

India's skill development journey has undergone a dramatic transformation over the past two decades. Until the early 2000s, the country's formal skilling infrastructure was predominantly shaped by Industrial Training Institutes (ITIs)—long-duration, state-run centres that were accessible to limited populations and often suffered from outdated pedagogies and low industry relevance. However, with accelerating economic liberalization and diversification, particularly the rise of the services sector and informal employment, the need for a more agile, responsive, and demand-driven skilling model became evident.

This transition spurred major national policy shifts toward modular, short-term, and outcome-linked training formats capable of rapidly equipping youth with job-ready skills. Major institutional milestones in this journey include:

- The creation of the National Skill Development Corporation (NSDC) in 2008 as a public–private partnership, envisioned to catalyze private investment and scale for-profit training in high-demand sectors
- The launch of the National Skill Development Policy (2009) and its 2015 revision, which institutionalized quality assurance mechanisms, encouraged cross-sector credit mobility, and mandated stronger employer engagement
- The formation of a dedicated Ministry of Skill Development and Entrepreneurship (MSDE) in 2014 consolidated fragmented initiatives into a central body responsible for overseeing national skilling strategies; and
- The launch of the flagship Skill India Mission in 2015, which brought skills development into public discourse and aimed to train over 400 million people by 2022 (Kumar et al., 2023)

Collectively, these interventions cultivated a more dynamic ecosystem of Training Providers (TPs), including not only government-run institutions but also private operators, NGOs, and hybrid industry-linked models. These providers now deliver compressed, demand-responsive courses mapped to the National Skills Qualification Framework (NSQF) and aligned with Sector Skill Councils (SSC) standards.

These landmark policies and institutional reforms gave rise to a diverse ecosystem of training providers. The next section examines how these providers are structured, accredited, and deployed to operationalize India's short-term training vision.

1.1.3 Structure and Functioning of Training Providers

At the heart of India's short-term skill training ecosystem are the Training Providers (TPs)—a diverse set of institutions responsible for delivering short-term skill training courses. These providers form the operational core of the skilling value chain, translating policy into practice by mobilizing youth, imparting sector-specific skills, and facilitating employment.

However, TPs don't operate in a vacuum. Their structure, accreditation, and delivery models are shaped by a mix of national guidelines and state-specific mechanisms. Before they begin operations, TPs must undergo a structured accreditation process, which includes infrastructure verification, compliance checks, and ongoing monitoring. This ensures that only capable and accountable institutions are entrusted with public skilling mandates.

Types of Training Providers

In West Bengal, state-sponsored short-term training typically involves two major categories of providers—Centre-Based and Industry-Integrated. Each type has its own operational logic, strengths, and limitations.

1. **Centre-Based Training Providers**

These are training centers that follow a government-approved framework. To qualify for targets, they must first secure Letters of Intent (LoIs) from prospective employers—formal commitments that indicate a demand for specific skills. The government then allocates training targets based on the strength of these commitments. This demand-driven model aims to align training with job market needs. However, in practice, these providers often stick to standardized curricula and operate in fixed institutional setups. Their engagement with employers is largely limited to the proposal stage, and they have less flexibility to adapt training in real-time based on industry feedback.

2. **Industry-Integrated Training Providers**

These providers are either run by or closely partnered with industry bodies. Their training is deeply embedded in actual workplace environments, often involving co-designed curricula, on-the-job training (OJT), and continuous industry inputs. Unlike their center-based counterparts, these providers are more agile, able to update content rapidly, align training with real-world expectations, and facilitate smoother transitions into employment.

1.1.4 Course Offerings and Sectoral Coverage

Courses offered under short-term skill training schemes are typically 80 to 600 hours long and are aligned with the National Occupational Standards (NOS) defined by Sector Skill Councils.

In West Bengal, the State Council of Technical & Vocational Education & Skill Development (WBSCTVE&SD) plays a central role in NSQF-aligned course development, enabling adaptations that meet specific local industry requirements. Training Providers and industries can also submit requisitions for new courses based on emerging needs. This information is drawn from the TET&SD Department's official website as well as corroborated through insights shared by state officials during field interactions.

1.1.5. Operational Flow of Short-Term Skill Training

The effectiveness of short-term programs lies not only in what is taught, but how it is implemented. Government schemes prescribe a structured operational model aimed at both standardization and efficiency. The following sections describe the operational flow as gathered from public sources and verified by the TET&SD Department, GoWB.

a. Setting up a Training Center

In West Bengal, for a Center-Based TP, the process of setting up training center under government skill development schemes involves meeting a set of infrastructure and operational prerequisites. TPs must first establish physical centers that comply with prescribed norms—this includes equipping classrooms and labs with sector-specific tools, ensuring adequate space, and maintaining safety and accessibility standards. Additionally, TPs are required to recruit qualified trainers with relevant industry experience.

In case of Industry-Integrated TPs, the training centers are setup in the industry premises with all the requisite infrastructure and equipment as per the course requirement. The trainers in this case are also mostly industry experts. These systems form the administrative backbone for scheme compliance and eligibility, enabling transparent reporting and performance tracking. This foundational setup is critical for TPs to get empaneled and begin mobilizing trainees under the skill schemes.

b. Mobilization of Candidates

Mobilization refers to the process of identifying and enrolling suitable candidates for short-term training programs. It typically begins with grassroots outreach through community networks, local government bodies, self-help groups, and awareness drives in villages and urban clusters. Beyond outreach, mobilization also involves structured counselling sessions to inform potential trainees about course content, employment prospects, and the expectations of both training and subsequent work opportunities. Effective counselling helps align candidate aspirations with program objectives, reduces the risk of dropouts, and improves adherence throughout the training cycle. By ensuring that trainees make informed choices, mobilization not only enhances the quality of classroom participation but also strengthens eventual placement outcomes, as candidates are more likely to complete training and transition into relevant employment.

c. Trainer Selection and Certification

Trainer quality is acknowledged as one of the most critical inputs. Trainers must undergo TOT (Training of Trainers) certification for Center-Based TPs and continuous skill upgradation to ensure learners are exposed to updated methods and industry-relevant curricula. For Industry-Integrated TPs, the Trainers are mostly industry experts with relevant industry knowledge.

d. Training Delivery, Assessment & Certification

Training comprises 60% theoretical and at least 40% practical content. Assessments are conducted by assessing bodies post verification of a minimum of 80% attendance by the candidates. Depending on the course, the assessing body can either be third-party agencies enlisted by relevant SSCs or the state council/s if recognized as assessing and awarding bodies by NCVET. For the state of West Bengal, most of the courses are now curated by the state council and the state council/s is also recognized as assessing and awarding bodies by NCVET.

e. Placement

Most of the central and state skill schemes now use outcome-linked funding, wherein a significant portion is disbursed only upon candidate placement. TPs often assist with job counselling, interviews, and entrepreneurship awareness—making the outcomes more meaningful and sustainable.

Overall, this highly structured yet diverse implementation model creates variation in performance. Examining the internal functioning of TPs across these operational stages offers key insights into what drives efficiency.

While the standardized model offers a clear roadmap for delivering the program, the unique challenges and realities on the ground influence how smoothly each provider can work through these steps. The following section explores these contextual factors in depth.

1.1.6. Structural and Operational Factors Shaping Training Provider Efficiency

In the context of public sector skill training, the concept of "efficiency" can be understood through several complementary lenses drawn from classic operations research and public management literature. As originally defined by Farrell (1957) and operationalized in DEA by Charnes, Cooper, and Rhodes (1978), efficiency consists of three key dimensions: technical efficiency, which refers to a provider's ability to maximize outputs (such as certified and placed trainees) from a set amount of inputs (including enrolled trainees, trainer experience, and course duration); allocative efficiency, which reflects the optimal utilization of inputs by considering their relative costs and benefits; and scale efficiency, which assesses whether the provider is operating at an optimal size to maximize productivity. For government-sponsored short-term skill training programs like the one studied here—where inputs are largely fixed by policy and budgetary constraints—the primary concern is technical efficiency, focusing on how well providers convert given resources into meaningful outcomes. Accordingly, this study adopts an output-oriented technical efficiency framework using DEA to benchmark and diagnose performance variations across training providers in West Bengal. This focus aligns with the prevailing approach in public sector performance evaluation, seeking to maximize societal returns on fixed investments through improved resource utilization and operational effectiveness (Farrell, 1957; Charnes et al., 1978).

This section outlines key systemic and institutional realities faced by government-sponsored training providers in West Bengal, helping explain the variation in efficiency observed across the dataset. These insights are based on information gathered from public sources, as well as direct interactions with training providers and consultations with officers from the TET&SD Department. While these factors do not directly affect DEA scores, they provide essential context for understanding inefficiencies or instances of standout performance.

Environmental Constraints and Institutional Diversity

Training providers operate in often starkly different environments. Urban and industry-linked centers generally enjoy better infrastructure, higher trainer availability, and proximity to employer networks. In contrast, rural or small-scale training providers frequently face operational limitations such as erratic power supply, unreliable internet connectivity, and limited access to skilled trainers. These resource disparities are not captured in DEA models but may significantly affect a provider's ability to deliver efficient outcomes using identical reported inputs.

Funding Delays and Administrative Overheads

Many Training Providers report delayed reimbursements, stringent reporting requirements, and overly bureaucratic fund release processes. These overheads often result in suboptimal expenditure timing—for example, delayed equipment upgrades or inability to conduct timely staff training. Although technical efficiency scores from DEA assess the input–output relationship at face value, behind-the-scenes administrative delays may depress actual capacity realization. This distinction between apparent and real efficiency is especially salient in public delivery ecosystems.

Gender and Social Inclusion

DEA efficiency scores in this study show a noteworthy pattern: providers with higher female participation exhibit relatively better efficiency. Though demographic composition is not included as an input in the DEA model due to data limitations, gender-inclusive environments often reflect deeper institutional strengths—such as strong counselling systems, safe training environments, and gender-sensitive pedagogy. These social inclusion variables, therefore, can serve as proxy indicators of organizational quality beyond technical measures.

These structural and operational factors underscore the need for a complementary qualitative approach. While DEA captures how efficiently providers utilize measured inputs, it offers little explanation for why some providers succeed while others falter. The qualitative strand of this study helps bridge that gap, exploring provider narratives, management practices, and organizational challenges to provide interpretive depth (Tashakkori & Teddlie, 2010; Braun & Clarke, 2006). As skills ecosystems are simultaneously technical and social, a mixed-methods design yields more comprehensive insights than standalone analysis.

1.2 Motivation for the Study

This study is shaped by both personal reflections and academic curiosity—grounded in a deep concern for how India prepares its youth for an uncertain and evolving job market. The idea first took root during field visits across West Bengal, where the author observed a recurring contradiction: training centers with high enrolment figures but weak outcomes in terms of certification, retention, or placements. The gap between surface-level compliance and real skill transformation was striking. What stood out even more was the diversity among Training Providers—some buzzing with structured processes and employer linkages, others struggling to deliver basic quality.

Academically, the research builds on a growing interest in performance evaluation methods across social sectors. While DEA has been widely applied in education, health, and banking, its use in India’s skill training context—particularly for comparing Training Provider efficiency—is still limited. By applying an output-oriented, variable returns to scale (VRS) DEA model to the short-term skill training landscape, this thesis contributes a much-needed methodological lens to understand who performs well, who doesn’t, and most importantly, why.

Equally motivating was the realization that numbers alone can’t tell the whole story. Many performance issues stem not just from measurable inputs and outputs, but from how providers work on the ground—their ability to mobilize candidates, maintain training quality, or build industry partnerships. This recognition led to the adoption of a mixed-methods approach, pairing DEA with in-depth qualitative insights to explore the lived realities behind the metrics.

1.3 Relevance of the Topic

The topic carries pressing real-world significance. Each year, flagship state and central skill schemes allocate thousands of crores to Training Providers across India. Yet, there's limited understanding of how effectively these investments is translated into meaningful employment outcomes. The issue isn't just about how many are trained or placed, but about how efficiently resources are being used—and where improvements can be made.

By identifying high and low-performing training providers, this study offers a tool for benchmarking. It also goes a step further by comparing different models of delivery—particularly Center-Based vs. Industry-Integrated TPs—to understand whether certain institutional forms or delivery models are inherently more efficient. This comparative angle is particularly relevant for policymakers at the national and state levels, who are tasked with designing, funding, and monitoring these systems.

By combining quantitative benchmarking with grounded qualitative insights, the research builds a more complete picture of what efficiency looks like in practice. The goal is not just academic—it's to help make the system more accountable, equitable, and impactful for the youth who depend on it.

In this study, "efficiency" primarily denotes technical efficiency—the ability of training providers to maximize key outputs, particularly the number of certified trainees, given inputs such as enrollment, trainer experience, and course duration. However, recognizing that short-term skill training success goes beyond certification, the research adopts a **mixed-methods lens**. Alongside DEA-based benchmarking, it incorporates qualitative insights on trainee satisfaction, and employer alignment. This dual approach not only quantifies performance but also captures critical dimensions of training quality, inclusiveness, and learner experience—offering a more holistic view of efficiency within West Bengal's diverse short-term skill training landscape.

Finally, while the study focuses on West Bengal, the framework developed here is scalable. It can inform similar assessments in other states or schemes, contributing to a more evidence-based and transparent skilling ecosystem aligned with the larger goals of the Skill India Mission, National Education Policy (NEP) 2020 and National Policy for Skill Development and Entrepreneurship 2025.

1.4 Scope of the study

This study is geographically focused on the state of West Bengal and draws upon data from 134 government-sponsored short-term skill Training Providers operating under state-funded skill development scheme. The analysis is restricted to programs aimed at youth aged 15–35 and excludes long-term technical education or informal apprenticeships.

Methodologically, the study uses an output-oriented Variable Returns to Scale (VRS) DEA model to assess the technical efficiency of Training Providers based on quantifiable input-output combinations. It is further enriched by qualitative data collected from both providers and certified trainees through structured interviews and thematic surveys. While the findings are specific to the selected sample and regional context, the analytical framework and policy implications may be relevant for broader application across similar state ecosystems or national schemes.

The study does not incorporate post-placement wage tracking or long-term livelihood outcomes, focusing instead on efficiency during the training-to-certification cycle. Environmental variables such as gender and caste composition are discussed for interpretive insights but are not part of the DEA input-output model.

1.5 Organization of the study

The thesis is structured into five chapters:

Chapter 1: Introduction provides the background, motivation, and rationale for the study, defines the scope and research gap, and outlines the organization of the thesis.

Chapter 2: Review of Literature examines existing scholarship related to skill development policies, training provider performance, efficiency measurement, and DEA applications in education and training sectors.

Chapter 3: Research Methodology outlines the research design, DEA model specifications, sampling approach, data sources, and qualitative protocols adopted in the study.

Chapter 4: Data Analysis and Interpretation presents and interprets the results of the clustering, DEA, tobit regression, and thematic analysis from both quantitative and qualitative perspectives.

Chapter 5: Conclusions and Recommendations synthesizes key findings, draws conclusions based on the research objectives, and provides actionable policy recommendations.

1.6 Summary

The introductory chapter laid the foundation for the study by tracing the evolution of India's skill development ecosystem and the operational realities of short-term Training Providers. It highlighted the performance challenges that persist despite large-scale public investment and policy attention.

The chapter also clarified the motivations behind the study, framed its relevance in light of current gaps in practice and scholarship, and positioned the chosen DEA and mixed-methods approach as a timely response to current needs. It concluded by outlining the scope and structure of the thesis, preparing the ground for a more detailed exploration of the existing literature in the following chapter.

CHAPTER 2: REVIEW OF LITERATURE

2.1 Introduction

2.2 Theoretical Foundations

2.2.1 Human Capital Theory

Gary Becker's (1964) Human Capital Theory conceptualizes education and training as purposeful investments that enhance individuals' productive capacity. In the context of short-term skill training, such investments enable participants to acquire market-relevant competencies, leading to higher certification rates, stronger employability outcomes, and measurable wage gains (Kumar et al., 2019; Bhatt et al., 2024). Within this study, the human capital lens provides a rationale for treating certification attainment as a key output variable, reflecting the extent to which Training Providers (TPs) effectively convert enrolments into employable, job-ready graduates.

2.2.2 Organizational Efficiency & Public Management

At the institutional level, theories of organizational efficiency—notably New Public Management (NPM) and Total Quality Management (TQM)—emphasize process optimization, resource stewardship, and accountability to stakeholders (Deming, 1986). These principles directly align with the methodological use of Data Envelopment Analysis, which benchmarks TPs against frontier peers to identify technical and scale efficiency. For publicly funded schemes such as Utkarsh Bangla, efficiency is not an abstract construct but an operational imperative: TPs are expected to maximize the impact of limited inputs (trainer expertise, course duration, enrolments) while ensuring high-quality outcomes for trainees.

2.3 Foundational Literature

2.3.1 India’s Skill Development Ecosystem: A thematic literature review

The India’s demographic profile—with more than 60% of its population in the working-age group (15–59 years) (United Nations Population Fund, 2023)—makes the development of a responsive, inclusive, and employment-linked skill ecosystem both a social and economic imperative. Over the past decade, the government has launched several national-level skilling initiatives, including PMKVY, DDUGKY, NSDC-backed training programs, and state-led innovations such as Skills Universities and Rural Self Employment Training Institute (RSETI). These interventions have primarily focused on short-term skill training, typically ranging from 15 days to six months, aiming to enhance employability, boost productivity, and stimulate entrepreneurship, especially among youth, women, and rural populations.

While the policy intent has been clear, the outcomes and operational performance of these programs remain a topic of extensive academic and policy scrutiny. This section synthesizes foundational literature that has evaluated the reach, quality, inclusiveness, and impact of India’s skill development efforts. These studies provide the contextual grounding for the current efficiency-based assessment of training providers.

Effectiveness of Short-Term Skill Training Program

- **Lamba & Makkar (2024),** highlighted three urgent priorities: first, ensuring that training programs produce the skills employers actually need; second, directing resources where they’ll make the biggest impact; and third, raising the bar on training quality.
- **Vageesha (2023)** concluded that the Skill India Mission plays a vital role in driving India’s economic growth and promoting social development. To overcome the challenges in its implementation, the government can focus on strengthening

infrastructure, encouraging greater participation from industry, and raising public awareness about the program.

- **Behera et al., (2025)** concluded that vocational education is still often viewed with lower regard and is seen as a last option for students with weaker academic performance. However, short-term initiatives like PMKVY have the potential to change this perception by opening up career-building opportunities, especially for young people from working-class backgrounds. With its focused approach to developing employability skills and helping participants transition into diverse job opportunities, PMKVY has played a significant role in driving its own success.
- **Verma (2024)** evaluated the effectiveness of the scheme in fostering career opportunities and generating employment for rural populations, with a particular focus on its implementation in Rajasthan. The study provides relevant insights for policymakers and implementing agencies to assess the scheme's impact and identify improvement areas. While the findings indicate promising outcomes—supported by positive case examples from regions such as Assam—significant gaps remain in execution. The author emphasized the necessity of continuous monitoring, improved implementation strategies, and adaptive policy measures to enhance the scheme's overall effectiveness.

Linkage to Study

The reviewed literature paints a compelling picture of India's evolving skilling landscape:

- Short-term, modular programs can improve employability and reduce underemployment
- Scheme-level performance is uneven across states and sectors, with documented gaps in post-placement support and retention.

- Recent emphasis on technology integration, gender inclusion, and state innovations suggests a shift toward more responsive and decentralized delivery models.

Yet, across this large body of work, few studies systematically examine training provider-level efficiency, particularly using DEA or mixed-method frameworks. This gap underscores the relevance and originality of the present study, which applies DEA to benchmark provider efficiency and integrates qualitative responses to unpack the drivers behind performance variation.

2.3.2 Understanding DEA: Conceptual and Methodological Evolution

The analysis of performance across decision-making units (DMUs) with multiple inputs and outputs is a longstanding challenge in fields like education, healthcare, banking, and public service delivery. Data Envelopment Analysis, first introduced in the late 1970s, emerged as a powerful non-parametric linear programming-based technique to address this issue. Unlike traditional econometric approaches that assume a specific functional form for the production process, DEA constructs an empirical efficiency frontier based on observed data and identifies how far each unit lies from this benchmark.

Over the past four decades, DEA has evolved significantly—both in its conceptual foundations and methodological sophistication. Early models focused on measuring technical efficiency under strict assumptions. Later developments introduced flexibility in scale, orientation, treatment of slacks, time dynamics, and statistical inference. These enhancements have made DEA particularly suitable for public programs like short-term skill training, where performance outcomes (e.g., certified trainees) are expected to be maximized relative to diverse resource constraints.

The following timeline traces the key milestones in DEA's evolution, contextualizing the model's relevance for efficiency analysis in India's skilling ecosystem.

Chronological Evolution of DEA: Foundational Models to Advanced Techniques

- **Charnes, Cooper, & Rhodes (1978)** introduced the CCR model, the foundational DEA approach under the assumption of Constant Returns to Scale (CRS). It enabled comparison of DMUs purely based on their ability to transform inputs into outputs. This model laid the mathematical basis for measuring relative efficiency using linear programming.
- **Banker, Charnes, & Cooper (1984)** extended DEA by developing the BCC model, which accounts for Variable Returns to Scale (VRS). This was a pivotal shift, as it distinguished pure technical inefficiency from scale inefficiency, thus allowing a more realistic evaluation of entities like training providers that may not operate at optimal scale.
- **Seiford & Thrall (1990)** compared input-oriented and output-oriented DEA models. While both yield the same efficiency frontier, they serve different decision contexts. For training programs aimed at maximizing outcomes like certifications or placements, output-oriented models are more appropriate.
- **Emrouznejad et al. (2008)** highlighted DEA's growing versatility, notably the emergence of:
    - Window analysis, allowing efficiency tracking over time (panel data).
    - Network DEA, evaluating performance in multi-stage systems.

  These extensions were crucial for making DEA adaptable to real-world service delivery.

- **Tone & Tsutsui (2009)** proposed the Slack-Based Measure (SBM) model, which integrated input and output slacks directly into the efficiency score. Unlike radial models that assume proportional adjustment, SBM addressed the case where inefficiencies are localized (e.g., underused trainers or underperforming placement cells).

- **Simar & Wilson (2011)** introduced bootstrapping methods for DEA, bringing statistical inference to what had been a deterministic technique. Their approach enables estimation of confidence intervals and bias correction in efficiency scores—essential for drawing reliable conclusions from policy research.
- **Cook & Zhu (2014)** advanced dynamic network DEA, incorporating both internal linkages across sub-processes and time-dependent performance. For example, a training provider's placement outcomes in one year may depend on mobilization efforts and trainer experience from the previous year.
- **Emrouznejad & Yang (2018)** synthesized DEA's global developments through a bibliometric review, emphasizing innovations in: Orientation (input vs. output), Returns to scale (CRS vs. VRS), Cross-efficiency models for peer-based benchmarking. Their review confirmed DEA's increasing adoption across education, health, social sectors, and public administration.

2.3.3 DEA Applications in Education and Skill Sector

The application of Data Envelopment Analysis has expanded significantly across public service domains, particularly in education, training, and health services. DEA's strength lies in its ability to evaluate the performance of institutions that consume varied resources (inputs) to deliver multidimensional outcomes (outputs), without requiring a specific production function. This makes it especially relevant for analyzing short-term skill training programs, where training providers differ in operational scale, infrastructure, trainer quality, and learner outcomes.

DEA has been widely used to assess the efficiency of educational institutions, skill development initiatives, and broader public interventions. This section synthesizes how DEA has been applied across these contexts, with a focus on the output-oriented Variable

Returns to Scale (VRS) model, which aligns with the goal of maximizing outcomes—such as the number of certified or employed trainees—given institutional constraints.

Few studies that applied DEA in Education Sector are given below -

- **Christina & Condez, (2024)** applied Data Envelopment Analysis to assess how efficiently 101 Philippine State Universities and Colleges (SUCs) operate. Her results enrich the ongoing conversation about higher education performance and offer practical guidance for policymakers, university leaders, and other stakeholders.
- **Thakur et al. (2024)** assessed how management education institutions in different parts of India perform compared to one another, and developed a comprehensive method for measuring efficiency that can be applied to higher education institutions in general
- **Liu et al., 2024** used the DEA Super-SBM Model to evaluate how efficiently higher education is delivered across 31 provinces in China. To understand differences in technology and practices among provincial groups, they applied the Meta Frontier approach to examine their technology gap ratios. Additionally, they used the Malmquist Productivity Index (MI) to track how higher education productivity changes over time in these provinces.
- **Yana Dolgikh (2023)** applied the output-oriented VRS DEA model to agricultural higher education institutions in Ukraine. They used the model to differentiate between efficient and scale-inefficient units, a practice that parallels training provider analysis in India.
- **Taleb et al. (2019)** estimated Returns to Scale for output-oriented integer DEA models for public universities in Malaysia. It calculates technical efficiency under constant returns to scale (CRS) and variable returns to scale (VRS), scale efficiency, and RTS categories.

- **Wang & Zhang (2023)** emphasized that VRS models are well-suited to assess DMUs operating across varied demographic and regional contexts, capturing true relative efficiency by adjusting for scale differences.
- **Fatimah & Mahmudah Umi (2017)** measured the performance efficiency of elementary schools in Indonesia, comparing CRS and VRS efficiency scores

While DEA has not yet been widely applied in peer-reviewed analyses of Indian skill development training providers, comparable international work does exist. For instance, Yu (2022) used a three-stage DEA model to evaluate efficiency in vocational skills training in China, and then related these efficiency scores to contextual drivers through regression analysis. This demonstrates the analytical potential of DEA in skill training settings and supports its use in benchmarking and performance diagnostics—functions central to the methodology of this thesis.

DEA vs. Traditional Evaluation Models

A recurring justification across studies is DEA's advantage over traditional evaluation frameworks such as the Kirkpatrick model, which rely on hierarchical, often subjective measures of training effectiveness (e.g., participant satisfaction, post-training behavior change).

- **Shero et al. (2021)** set out to explain Data Envelopment Analysis as a research methodology, using an example from the education sector. Their study demonstrates how DEA can be applied to assess the efficiency with which children convert their reading-related skills into actual reading comprehension. In doing so, they also argue that DEA can be a particularly valuable choice for certain types of research questions.
- **Shimshak & Wagner (2012)** demonstrated that DEA is both feasible and practical for examining state systems of higher education, offering valuable insights for

identifying “best practice” systems and providing guidance for improvement. They also highlighted the relevance of DEA modeling for state policymakers and education researchers

- **Ruiz & Sirvent (2020)** pointed out that DEA provides peer comparisons and improvement targets, unlike the Kirkpatrick model, which is limited to descriptive evaluation.
- **Anderson & Johnson (2023)** emphasized DEA’s statistical robustness, making it better suited for policy-level decisions compared to Kirkpatrick, which relies on softer indicators.
- **Singh et al., (2022)** applied DEA to higher educational institutions and noted “DEA’s ability to accommodate multiple–sometimes incommensurable–outputs (like placements, skill upgrades, research, etc.) is a prime advantage over other traditional approaches.” The methodology allows the inclusion of outputs such as student certification rates, employment/placement data, and measured skill enhancements within a unified evaluation model.
- **Dyson et al., (2001)** argued that DEA can identify scale efficiency, helping providers understand whether they are operating at an optimal scale—something traditional evaluation models don’t capture.
- **Coates & Lamdin (2002)** praised DEA’s ability to track performance over time, supporting longitudinal assessments that static models like Kirkpatrick often lack.

Linkage to Study

DEA—especially in its output-oriented VRS form—has emerged as a preferred tool for evaluating the performance of educational and skill training institutions. Its ability to:

- Handle multiple inputs and outputs
- Account for scale heterogeneity, and

- Deliver actionable peer-based benchmarking,

makes it more robust than traditional evaluation models for contexts like India's skilling ecosystem.

2.3.4 Input–Output Selection in DEA and handling multicollinearity

In Data Envelopment Analysis the selection of input and output variables is a critical step that directly influences the validity and discrimination power of the efficiency scores. Since DEA is a non-parametric method, it is highly sensitive to the dimensionality and correlation structure of the dataset. Including too many or poorly chosen variables can lead to overfitting, reduced discrimination among DMUs, and misinterpretation of efficiency.

For studies assessing short-term skill training providers, where inputs might include trainee enrolment, trainer qualifications, and course duration, and outputs focus on certifications or placements, it becomes essential to use statistical techniques and expert judgment to ensure that selected variables are meaningful, non-redundant, and aligned with the research objective.

Literature on Input–Output Selection and Multicollinearity Handling

- **Cook et al., (2014); Dyson et al., (2001); Golany & Roll (1989); Wagner & Shimshak (2007)** emphasized that variable selection in DEA should reflect decision-maker priorities and contextual relevance, cautioning that inclusion of irrelevant variables or redundant dimensions can distort efficiency outcomes. They stress the importance of appropriate data transformation and expert consultation during model design. It also focused on using correlation analysis to detect multicollinearity among input variables.
- **Chen et al. (2022)** demonstrated the use of the Shannon entropy technique for DEA variable selection. This method quantifies the variability and information content

of each candidate variable and selects those that improve the discrimination power of the model. They also address issues of negative or scale-incompatible data

- **Zubir et al., 2024** in their review of hospital-based DEA studies, identified four commonly used approaches for input–output selection:
    - Literature review
    - Data availability
    - Expert judgment
    - Systematic statistical methods

  These are often used in combination to ensure model robustness

- **Huang (2017)** applied the DEMATEL technique (Decision-Making Trial and Evaluation Laboratory) to study causal relationships between inputs and outputs. They combined this with Pearson correlation analysis to identify and reduce multicollinearity—a key issue in skill training studies where variables like training cost and course duration may be highly correlated
- **Hashemi Petrudi et al (2022)** used the Fuzzy Delphi Method to incorporate expert insights while reducing subjectivity in input-output variable selection. This method is particularly useful when quantitative data is limited or noisy, as is often the case in public training systems
- **Wong (2021)** proposed a global search method to identify the most influential input–output variables. Their approach measures the effect of adding or removing each variable on average efficiency scores across DMUs.
- **Davis & Johnson (2022)** focused on using correlation analysis to detect multicollinearity among input variables. They recommended removing or consolidating variables when correlations exceed 0.8—a standard threshold used in empirical DEA studies.

- **Seiford & Thrall (1990)** highlights the impact of redundant (highly correlated) variables on discriminatory power of DEA

Linkage to Study

Given the diversity and interdependence of variables in skill development (e.g., course duration, training cost, trainer experience), this study:

- Used Pearson correlation to identify and drop highly correlated variables
- Applied expert judgment to prioritize policy-relevant dimensions like certification rates
- Retained variables with distinct conceptual meaning, ensuring no duplication of effort or measurement

For instance, here "training cost per trainee" and "course duration" are highly correlated ($r > 0.85$), the course duration input was retained. Here although the cost per trainee is fixed by as common cost norms, the actual cost that the training provider is spending on the trainee cannot be gauged/ and is not available. Similarly, "number of trainees placed" was be excluded as it overlapped too strongly with "number certified" where placement is not always perceived as a clear output indicator.

A well-designed DEA model hinges on thoughtful and theoretically grounded input-output variable selection. Literature emphasizes:

- Reducing multicollinearity,
- Using hybrid methods (statistical + expert-based), and
- Focusing on policy-relevant, measurable indicators

These principles guide this study’s modeling choices, ensuring that the resulting efficiency scores are both analytically valid and actionable for policymakers and training providers.

2.4 Empirical Literature and Research Gaps

While the foundational literature establishes the theoretical and methodological basis for using Data Envelopment Analysis (DEA) in efficiency measurement, it is the empirical literature that brings to light how these methods are applied in real-world settings—especially in education, technical training, and skill development. This section critically reviews existing empirical research to understand (i) both the extent and limitations of current DEA applications in evaluating training providers, particularly within developing countries and short-term skilling contexts and (ii) research done on short-term skilling ecosystem.

The review unfolds across three domains:

- First, it summarizes DEA-based studies in technical/vocational education.
- Second, it zooms in on India-specific literature on short-term training programs, all of which are non-DEA but provide critical insights into institutional practices, trainee experiences, and program design.

The ultimate goal is to identify what these studies reveal, what they miss, and how this research addresses those gaps.

2.4.1 DEA Applications in Skill ecosystem

Although DEA has been extensively applied to evaluate efficiency in various education and training contexts, there is a notable absence of studies employing this approach to assess the performance of short-term skill training providers (STSTPs), particularly within the Indian skill development landscape. A review of the literature identified only three tangentially related studies. Achi (2020) examined the technical efficiency of public vocational institutions in Algeria’s Batna province, yet the analysis was geographically limited and did not distinguish between institutional types or delivery modes. Fatimah and Mahmudah Umi (2017) applied DEA to elementary schools in Indonesia, a substantially different educational context, and did not incorporate qualitative methods to enrich the analysis. Fazlollahtabar and Ebadi (2023) utilised a network DEA framework to evaluate the skill training supply chain, focusing on system-level efficiency rather than the performance of individual training providers. The scarcity of provider-level DEA applications in short-term skill training represents a clear research gap, which this study addresses through the use of an output-oriented DEA model, complemented by qualitative inquiry to explain observed efficiency patterns.

Table 2.1: Literature reviewed on DEA Applications in Education, Technical Education, and Training Efficiency

Sl. No.	Type	Title Details	Author(s) & Year	Gist	Research Gap
1	Journal Article	The efficiency of public vocational institutions by DEA: case of VTACs of Batna province, Algeria	Achi (2020)	The study evaluates the technical efficiency of public vocational institutions in the Batna province of Algeria using the Data Envelopment Analysis approach, focusing on vocational training and apprenticeship centers (VTACs). Input-output data were used to compute efficiency scores and offer recommendations	Examines only public VTACs in a single province and does not disaggregate results by different institutional types or education delivery modes. The scope is provincial rather than national.

Sl. No.	Type	Title Details	Author(s) & Year	Gist	Research Gap
				for improving institutional performance	
2	Journal Article	Two-Stage Data Envelopment Analysis for Measuring the Efficiency of Elementary Schools in Indonesia	Fatimah & Mahmudah Umi, (2017)	Measured the performance efficiency of elementary Schools in Indonesia	Lack of mixed method
3	Journal Article	Design of Efficient Skill Training Supply Chain using Network Data Envelopment Analysis	Fazlollahtabar, H. & Ebadi, S. (2023)	This study designs and evaluates the supply chain for skill training using a network data envelopment analysis (NDEA). It analyzes efficiency at multiple layers within the skill training ecosystem, emphasizing the critical role of skill centers in workforce empowerment and employability	Does not analyse the performance of skill training providers

2.4.2 Literature on Indian Short-Term Skill Training Providers

While empirical applications of DEA in the Indian context remain limited, there is a growing body of research examining various dimensions of short-term skill training programs like PMKVY and DDU-GKY. The studies listed in the table above offer insights into implementation challenges, dropout patterns, trainee satisfaction, and placement outcomes—often using survey data, administrative records, or qualitative interviews.

However, despite their relevance, most of these studies:

- Do not attempt to measure efficiency in a structured or comparative way
- Treat training providers as black boxes without benchmarking or classification
- Rely primarily on subjective feedback or fragmented output indicators without linking them to institutional characteristics or resource use

These gaps underscore the need for a more systematic approach to evaluating performance—especially one that captures how efficiently providers convert inputs into certifiable outcomes. The current study aims to address this by applying DEA to benchmark training providers, while integrating the kind of qualitative feedback that these studies bring forward.

Table 2.2: Literature of Short-Term Skill Training

Sl. No.	Type	Title Details	Author(s) & Year	Gist	Research Gap
1	Journal Article	Issues and challenges in implementing the Skill India movement: Training partner perspective	Mukherjee & Basu (2021)	Examined PMKVY implementation issues from the training partner perspective; focused on mobilization and placement tracking.	No efficiency assessment; limited to administrative and compliance-level analysis.
2	Journal Article	Short Run Effects of Skill Training for the Unemployed Youth in India	Barua et al (2022)	Used administrative data to analyse the impact of DDUGKY program and concluded a growth in wage	Dependent on Administrative data, No Training Provider Study to account for different outcomes for

Sl. No.	Type	Title Details	Author(s) & Year	Gist	Research Gap
				employment post training	different Training Providers
3	Journal Article	Skills Training and Employment Outcomes in Rural Bihar	Chakravorty & Bedi (2021)	Used training provider data to assess placement outcomes in DDUGKY centers	Focused only on output-side analysis; no benchmarking of provider performance.
4	Journal Article	Short-Term Vocational Courses as a Career-Building Program for the Youth in Chhattisgarh, India	Behera & Tarai (2024)	Gauges young people's perception of PMKVY as a career-building program	No training provider study
5	Journal Article	Bridging the Skill Gap to Reduce Attrition: The Role of PMKVY in Enhancing Workforce Retention in Semi-Formal Sectors	Shinde (2025)	Case study of PMKVY's impact on job satisfaction and retention in semi-formal workforce	Focus on retention and individual outcomes; no efficiency or benchmarking.
6	Journal Article	Skill Development Programmes: Challenges and Employment Opportunities	Kumar & Hooda (2024)	Reviews trainee perspectives on challenges and employment in skill programs	Focus on employment perception; no provider benchmarking.
7	Journal Article	Perception Of Training Partners Towards Skill Development and Training Outcome at Implementation Stage of PMKVY Program: An Empirical Study	Balakrishnan & Senthilkumar (2020)	Surveyed PMKVY and NSDC training partners trainees on training content, trainer effectiveness, and infrastructure.	No linkage to institutional characteristics or efficiency metrics.
8	Journal Article	A Study on Impact of Skill India on Rural Youth of North East India	Kumar & Shobana (2023)	Qualitative study highlighting contextual barriers in skilling delivery in remote regions.	Context-rich, but does not generalize or benchmark provider types or models.
9	Journal Article	Analysis of Tribal youth Perception towards Skill development (YTC) Training	Venkatarao & Murthy (2022)	Used Likert-scale surveys to analyse candidate satisfaction with trainers, content, and job readiness.	Focused on learner perceptions only; did not analyse institutional performance.

2.5 Research Gaps

The review of both global and Indian literature reveals several important gaps—methodological, contextual, and analytical. These gaps are not merely academic but have direct implications for how policymakers and practitioners understand the performance of short-term skill training programs.

2.5.1 Gaps in DEA-Based Efficiency Literature

While DEA has become a widely accepted tool for assessing efficiency in education, its application to skill training—especially in complex, mixed-provider systems like India's—remains limited and methodologically constrained. The overall key gaps identified are:

- **Input-dominant orientation**: Most DEA studies in the education domain prioritize input-oriented models (e.g., Almeida et al., 2025; Mergoni et al., 2025) which focus on minimizing resources. However, for government-funded training schemes with fixed inputs and policy-defined targets, an output-oriented approach—focused on maximizing certifications or placements—is far more relevant.

- **Neglect of scale variation**: Many studies use models assuming constant returns to scale (CRS), overlooking institutional diversity. Only a few apply variable returns to scale (VRS), which are essential in comparing providers of vastly different sizes and scopes.

- **Little use of mixed DEA techniques**: Method like second-stage Tobit regressions is underutilized, even though they offer richer diagnostics and policy-relevant insights (Eren & Aydın, 2025;).

- **Lack of qualitative triangulation**: The "why" behind inefficiency scores is frequently unexplored. Studies rarely supplement DEA with stakeholder interviews, feedback, or institutional case evidence.

- **Sparse Indian representation**: Despite the presence of a vast national skilling ecosystem, no studies employing DEA to evaluate India's short-term training providers could be identified in the reviewed literature.

Together, these gaps point to the need for context-appropriate DEA frameworks that are both scale-sensitive and outcome-focused, and that integrate quantitative benchmarking with on-ground perspectives.

2.5.2 Gaps in Literature on India's Short-Term Skill Training Providers

Indian studies on PMKVY, DDU-GKY, and related skilling schemes offer important insights, but are often fragmented in design and narrow in analytical depth. The key limitations observed are:

- **Lack of performance benchmarking**: Most studies assess satisfaction, dropout, or placement independently, but do not benchmark providers against each other using standardized models like DEA

- **Neglect of TP-type comparison**: Studies rarely distinguish between Industry-Integrated and Center-based models, despite the clear differences in how these providers are structured and funded.

- **Regional and programmatic silos**: Most studies are scheme-specific and lack generalizability across the broader ecosystem.

- **Limited mixed-methods approaches**: While quantitative or qualitative studies exist in isolation, few have attempted to combine both strands to offer a comprehensive understanding of training delivery and outcomes.

These gaps reinforce the need for an evaluative approach that combines efficiency benchmarking with stakeholder-grounded qualitative data, providing a richer picture of training provider performance in India's dynamic skilling landscape.

2.6 Research Gaps

In light of the gaps identified across both the global DEA literature and India-specific skill training studies, this research makes several distinct contributions—methodologically, contextually, and analytically.

1. **Adoption of an output-oriented VRS DEA model**: Most existing studies rely on input-oriented or CRS-based models, which are less suited to the performance-driven nature of short-term skill training schemes. This study adopts an output-oriented Variable Returns to Scale (VRS) approach, which better reflects the operational realities of government-funded programs where outcomes like trainee certification are emphasized, and input constraints are predefined.

2. **Comparative benchmarking of TP types**: Existing literature tends to treat the short-term training delivery models as homogeneous groups. This study distinguishes between the two training delivery models - enabling more nuanced benchmarking and operational insights.

3. **Integration of qualitative data from trainees and training providers**: Unlike most studies conducted to evaluate the impact of short-term training schemes, this research combines quantitative benchmarking with qualitative feedback from certified trainees and institutional heads. This allows for a deeper understanding of not just how efficient providers are, but why they perform the way they do.

4. **Focus on India's under-researched STT ecosystem**: While DEA has been widely applied in global contexts, there is limited application in India's short-term skilling sector. This study focuses on Short-Term Skill Training Providers covering a diverse sample of providers—addressing a critical void in the empirical literature.

5. **Policy relevance and practice-level insights**: By combining efficiency scores with ground-level narratives, the study offers actionable insights for program administrators, policymakers, and training partners. These include best practices, inefficiency drivers, and potential levers for improving institutional performance in a decentralized skilling ecosystem.

2.7 Conceptual Framework

The conceptual framework for this study is informed by both the foundational theory of Data Envelopment Analysis and the empirical review of short-term skill training provider performance. It integrates the efficiency assessment model with contextual features drawn from training operations and stakeholder perspectives.

At its core, the framework is structured around the DEA input-output model, with an output-oriented Variable Returns to Scale (VRS) assumption. The DEA component is supported by a qualitative feedback loop—linking the observed efficiency scores with real-world insights from both certified trainees and training providers.

Table 2.3: Conceptual Framework for DEA-Based Efficiency Assessment of Training Providers

Layer	Component	Description
Input Variables	I1: Number of Trainees Enrolled I2: Average Experience of Trainers I3: Average Course Duration (in hours)	These reflect the operational scale and quality inputs of a training center.
Output Variable	O1: Number of Certified Trainees	Represents the primary desired outcome under public skilling schemes

Layer	Component	Description
DEA Model	Output-oriented VRS Model	Focuses on maximizing certification outputs given fixed or standardized inputs across providers.
Qualitative Integration	Trainee & TP Feedback on Training Quality, Infrastructure, Trainer Support, Challenges	Used to interpret DEA results and identify non-quantitative factors influencing performance.

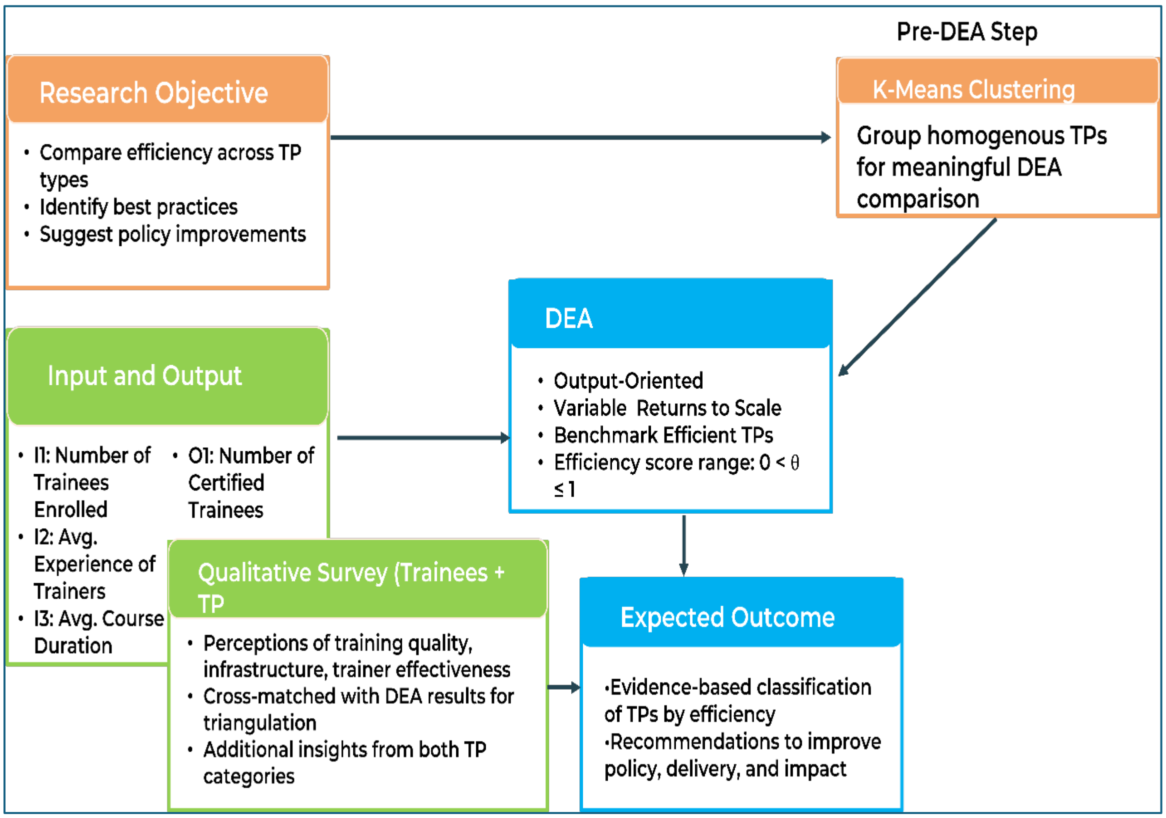

Figure 2.1: Conceptual Framework for DEA-Based Efficiency Assessment of Training Providers

2.8 Summary

This chapter set the foundation for the present study by reviewing both theoretical and empirical literature relevant to the efficiency assessment of short-term skill training providers.

The first half of the chapter focused on the foundational concepts of Data Envelopment Analysis —its evolution, model variants, orientation types, and applications across education and public sector efficiency studies. This provided the analytical backdrop for selecting an output-oriented VRS DEA model, which aligns with the structure and goals of Indian government-funded training schemes.

The second half of the chapter reviewed empirical studies, drawing insights from both international DEA applications in education/training and India-specific evaluations of skilling schemes. While global DEA studies have shown methodological maturity, they largely neglect contextual interpretation and provider diversity. Conversely, Indian studies tend to focus on trainee satisfaction, dropouts, or placement outcomes, but lack systematic benchmarking or efficiency analysis.

This review uncovered significant research gaps—including the need for output-oriented DEA models, provider-type comparisons, and integration of qualitative feedback. In response, the study positions itself to bridge these gaps through a comparative, mixed-method DEA analysis of Short-Term Skill Training Providers.

The chapter concluded by outlining the conceptual framework, which brings together DEA-based efficiency benchmarking with qualitative insights from certified trainees and training providers—ensuring a more holistic understanding of institutional performance.

Together, these insights provide the foundation for the research design and methodology, which will be discussed in the following chapter.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodological framework adopted to evaluate the efficiency of short-term skill training providers (TPs) operating under government-led initiatives in West Bengal, India. The study employs an explanatory sequential mixed methods design, integrating quantitative efficiency analysis with qualitative stakeholder insights. This design allows for a comprehensive examination of what efficiency gaps exist among TPs and why certain providers perform better than others.

The first phase involves a quantitative assessment using Data Envelopment Analysis under an output-oriented Variable Returns to Scale (VRS) framework, enabling the identification of efficient and inefficient providers. The second phase consists of qualitative surveys with training providers and certified trainees, aimed at contextualizing the efficiency scores and uncovering operational practices, challenges, and perspectives that influence outcomes.

Grounded in a pragmatic research paradigm, this methodology supports the triangulation of findings and the generation of meta-inferences. By combining statistical benchmarking with real-world narratives, the chapter establishes a robust foundation for deriving policy-relevant insights and practical recommendations to strengthen India's skilling ecosystem.

3.2 Research Question

The present study is guided by the following research questions:

- **RQ1:** How efficient are training providers (TPs), relative to the DEA frontier, in converting inputs into certified training outcomes?
- **RQ2:** What operational characteristics and institutional practices differentiate efficient TPs from their inefficient counterparts?

- **RQ3:** How do certified trainees perceive their training experience, and do these perceptions vary based on the efficiency level of their training provider?

3.3 Research Problem

India’s skilling ecosystem, though ambitious in scope, continues to face systemic inefficiencies that hinder its ability to deliver consistent, outcome-oriented training across providers. Government-led initiatives such as the Pradhan Mantri Kaushal Vikas Yojana (PMKVY) and DDU-GKY have expanded access to short-term training, yet wide disparities persist in performance across training providers (TPs). Some institutions consistently convert inputs—like enrolled trainees, training hours, and trainer expertise—into certified outputs, while others struggle despite operating under similar guidelines.

A core issue is the absence of structured benchmarking and feedback mechanisms. There is no formal system to identify best-performing TPs or disseminate operational practices that drive efficiency. Consequently, underperforming providers lack reference points or data-driven insights needed for improvement. Moreover, while quantitative evaluations often capture what outcomes are achieved, they rarely explain why certain providers succeed where others falter.

To address this gap, the present study applies Data Envelopment Analysis to evaluate the technical and scale efficiency of 134 training providers in West Bengal. The study further integrates qualitative insights from TPs and certified trainees to explain the efficiency scores and reveal the operational, instructional, and institutional factors that contribute to performance variations. By doing so, it seeks to generate evidence-based recommendations for a more effective and equitable skill development ecosystem.

3.4 Research Objectives

The overarching aim of this study is to evaluate and explain the efficiency of short-term skill training providers operating under government-sponsored programs. Through a mixed methods approach, the study seeks to combine statistical benchmarking with stakeholder perspectives to derive actionable insights.

The specific research objectives are as follows:

- To identify the best practice benchmarks for different skill training providers using efficiency frontier
- Compare efficiency distributions between Center-based Training Providers vs. Industry-Integrated Training providers to determine which model delivers greater productivity and can be replicated nation-wide
- To understand how skill training programs can be scaled up by learning from the best in the market.
- Distill best practices from the most efficient TPs and propose actionable guidelines for government and training partners to elevate under-performing providers
- Policy and practice guidelines tailored to under-performing short-term training providers

3.5 Theoretical Framework and Model adopted

This study is anchored in the pragmatic research paradigm, which supports the use of mixed methods to address complex, real-world problems. The core assumption is that no single methodological approach is sufficient to fully understand multifaceted institutional performance. Accordingly, the study adopts an explanatory sequential mixed methods design (Creswell & Plano Clark, 2017), in which quantitative analysis is conducted first, followed by qualitative inquiry to explain and contextualize the numerical findings.

The quantitative phase applies Data Envelopment Analysis to evaluate the technical and scale efficiency of training providers. DEA is rooted in production theory, where Decision-

Making Units (DMUs) are assessed based on how efficiently they convert inputs (number of trainees, trainer experience, course duration) into outputs (certified trainees). The study uses an output-oriented Variable Returns to Scale (VRS) model, as the goal is to maximize outcomes given limited resources. To further explore environmental influences on efficiency, a Tobit regression is used as a second-stage analysis, suitable for censored dependent variables like DEA scores.

The qualitative phase explores stakeholder perspectives through surveys with training providers and certified trainees, aiming to identify operational practices, challenges, and institutional behaviours associated with efficiency. This phase is guided by principles from implementation science and organizational learning theory, which stresses the importance of contextual and experiential knowledge in shaping institutional performance.

Together, the mixed methods design allows for triangulation, complementarity, and explanation, thereby enabling the development of robust, meta-inferential insights. The dual framework—quantitative benchmarking and qualitative interpretation—provides a comprehensive lens for understanding and improving the skill development ecosystem.

3.5a Definition of Constructs and Moderating Variables

This study uses distinct sets of constructs in its quantitative and qualitative strands, consistent with the mixed methods design.

Quantitative Constructs (for DEA)

The DEA model evaluates each training provider as a Decision-Making Unit (DMU) transforming inputs into outputs. The constructs used are:

- **Inputs:**
    - Number of Trainees Enrolled – represents operational scale

    - Average Experience of Trainers (years) – captures the quality of trainer
    - Average Course Duration (hours) – indicates training intensity and comprehensiveness

- **Output:**
    - Number of Trainees Certified – reflects the primary outcome measure under government training mandates

Initial consideration was given to "Average training cost per trainee" and "Number of trainees placed," but these were excluded after correlation analysis revealed high redundancy with retained variables (please refer Table 3.1). This step ensures discriminatory power in the DEA model and avoids multicollinearity.

Contextual Moderators (for Tobit Regression)

To explore factors associated with variations in efficiency scores, the following moderating variables were introduced in the second-stage Tobit regression:

- % of Female Trainees
- % of SC/ST/OBC Trainees

These variables are not controllable by providers but may affect efficiency outcomes due to structural or demographic conditions.

Qualitative Constructs

The qualitative surveys with training providers and certified trainees explore themes such as:

- Training delivery quality

- Infrastructure availability
- Trainer role/competence
- Mobilization challenges/Strategies
- Counselling and placement practices/challenges
- Trainee satisfaction and perceived job readiness

These constructs are explored inductively through thematic analysis.

3.5b Hypothesis Formulation

This study takes an open and exploratory approach rather than testing strict hypotheses from the start. Instead of starting with fixed expectations or theories, it asks broad questions to understand how different factors like gender balance, social groups, or training methods might relate to performance differences. The quantitative analysis looks for any statistical connections, while the qualitative part listens to stakeholders' experiences without assumptions, letting insights naturally emerge about how things really work on the ground. This flexible method fits well with the mixed-methods design, blending numbers and stories to build a deeper, more meaningful understanding tailored to the specific context

3.6 Research Design

This study adopts an explanatory sequential mixed methods research design (Creswell & Plano Clark, 2017), in which a quantitative phase precedes and informs a qualitative phase. The rationale for this design lies in the dual objectives of the research: (a) to measure the efficiency of training providers using quantitative benchmarks, and (b) to explain the operational, institutional, and experiential factors behind the observed efficiency patterns.

3.6.1 Mixed Methods Design: Explanatory Sequential

In this design, the research process unfolds in two distinct but connected phases: an initial quantitative phase that identifies patterns and outliers, followed by a qualitative phase that seeks to explain those findings with contextual depth and stakeholder narratives.

In Phase I, a Data Envelopment Analysis is used to evaluate the efficiency of 134 short-term skill training providers (TPs) across West Bengal. The DEA model identifies relatively efficient and inefficient providers based on their ability to convert inputs (trainee enrolment, trainer experience, course duration) into output (certified trainees)

Informed by the DEA results, Phase II employs qualitative surveys with selected TPs and certified trainees, purposively sampled across efficiency tiers and training models. These instruments elicit narrative responses on institutional practices, implementation challenges, and perceived quality of training.

This two-phase structure enhances both breadth and depth: the quantitative strand offers generalizability and objective benchmarking, while the qualitative strand provides meaning and explanatory power. The sequential nature ensures that the qualitative exploration is grounded in empirical patterns, and that integration occurs not only at the interpretation stage but also through strategically aligned data collection.

3.6.2 Integration Strategy: Meta-Inference and Triangulation

The two phases of this mixed methods study are integrated through a structured process of meta-inference development, which enables the synthesis of quantitative and qualitative findings into unified, actionable insights (Venkatesh, Brown, & Bala, 2013). This is central to the explanatory sequential design, where the qualitative phase is explicitly informed by the quantitative results, and both strands contribute to the final interpretation.

Three primary strategies of integration are employed:

1. Bridging

Bridging involves aligning findings across the quantitative and qualitative strands to identify areas of convergence. For example, if training providers that rank highly on DEA efficiency scores also report frequent engagement with industry partners or proactive placement strategies in qualitative responses, the bridge between metrics and practice becomes evident. This strengthens the credibility of both strands and supports policy recommendations grounded in empirical and experiential data.

2. Bracketing

Bracketing acknowledges and interprets contradictions between strands. If a provider appears efficient in the DEA model but highlights major infrastructure or mobilization challenges in their qualitative narrative, such discrepancies are not dismissed. Instead, they are analysed to uncover hidden issues or important factors that standard efficiency measures might miss.

3. Use of Joint Displays

To operationalize integration, joint display matrices are used to compare thematic patterns across DEA-defined efficiency tiers. For instance, training providers were categorized by PTE score thresholds (e.g., ≥ 0.85 = High Performing TPs), and their qualitative responses were coded and analysed to detect systematic differences in practices or challenges.

This integrated approach supports triangulation (Denzin, 1978), enhances inference quality (Teddlie & Tashakkori, 2009), and ensures that the study does not merely report parallel findings, but combines them to generate deeper, policy-relevant insights.

3.6.3 Rationale for Mixed Methods Approach

The choice to adopt a mixed methods design is guided by both the nature of the research questions and the limitations of relying solely on quantitative or qualitative approaches. Short-term skill training programs operate at the intersection of institutional, pedagogical, and socio-economic factors. Hence, understanding how efficiently providers function (quantitatively) and why such differences occur (qualitatively) requires a design that combines breadth of measurement with depth of interpretation.

Following Creswell (2003) and Greene et al. (1989), this study aligns with seven recognized purposes of mixed methods research:

- **Complementarity** (enhancing meaning)
- **Completeness** (capturing all relevant dimensions)
- **Developmental** (using one strand to inform the other)
- **Expansion**
- **Corroboration/confirmation**
- **Compensation**, and
- **Diversity** of perspectives (Tashakkori & Teddlie, 2008)

The quantitative strand uses DEA to benchmark training provider performance based on objective input–output ratios. However, DEA results alone do not explain why certain providers outperform others. Hence, the second, qualitative strand explores institutional strategies, implementation challenges, and stakeholder experiences. This aligns with the developmental and explanatory intent of the study.

Importantly, the approach also draws from Teddlie and Tashakkori's (2009) framework on mixed methods inference quality. The research process ensures:

- **Design Quality**: Alignment of questions, methods, and analysis;
- **Interpretive Rigor**: Reflexive treatment of sampling and response bias (e.g., self-selection in TP responses);
- **Integration Quality**: Triangulation and bracketing to handle convergence and contradiction across strands.

The qualitative data are purposefully linked to the DEA results—for instance, comparing provider responses across efficiency tiers. Such integration enhances meta-inference quality, supporting conclusions that are both empirically grounded and contextually valid.

3.7 Quantitative Design – DEA Specification and Execution

3.7.1 DEA Model and Efficiency Frontier Construction

To assess the performance efficiency of short-term skill training providers (TPs), the study employs Data Envelopment Analysis, a non-parametric method based on linear programming that benchmarks Decision-Making Units against a "best-practice frontier." DEA is particularly suited for public service settings where multiple inputs and outputs must be simultaneously considered (Charnes, Cooper, & Rhodes, 1978; Banker, Charnes, & Cooper, 1984). In this study, the Training Providers serve as the Decision-Making Units (DMUs) for the Data Envelopment Analysis. Each provider represents an individual unit whose relative efficiency in delivering skill development programs is assessed based on multiple input and output variables.

This study uses an output-oriented Variable Returns to Scale (VRS) DEA model, aligning with the core objective of government-sponsored skill training — to maximize certified trainees given available resources. The VRS model is preferred because it recognizes that

TPs may not operate at optimal scale, especially in resource-constrained contexts. This output-oriented VRS DEA model not only maximizes trainee certification—mirroring human-capital returns on training investments—but also aligns with public-management metrics of outcome-efficiency under variable scale.

Output-Oriented DEA Logic

The output-oriented model seeks to determine by how much a TP can proportionally increase its outputs, keeping input levels fixed. In this case, a training provider is considered efficient if it cannot increase the number of certified trainees without increasing its inputs.

DEA Formulation (Output-Oriented, VRS)

This study employs an output-oriented DEA model under Variable Returns to Scale (VRS) assumptions. The output orientation reflects the policy priority of maximizing training outcomes (certified candidates) given fixed resource constraints, while VRS accommodates the diverse scales of operation among training providers.

The mathematical formulation for the output-oriented VRS model is:

Maximize φ

Subject to:

- $\Sigma_j \lambda_j x_{ij} \leq x_{io}, \forall i = 1,...,m$
- $\Sigma_j \lambda_j y_{rj} \geq \varphi y_{ro}, \forall r = 1,...,s$
- $\Sigma_j \lambda_j = 1$
- $\lambda_j \geq 0, \forall j$

Where:

- φ represents the efficiency score ($\varphi \geq 1$; $\varphi = 1$ indicates efficiency)

- x_{ij} and y_{rj} are inputs and outputs for DMU j
- λ_j are intensity variables for peer DMUs
- The constraint $\Sigma_j \lambda_j = 1$ ensures VRS

An efficient DMU lies on the production frontier and scores 1. Inefficient units are ranked by the proportional increase in outputs they would need to match efficient peers under VRS assumptions.

Pure Technical Efficiency Score (PTE) is then calculated for each DMU by the formula:

$PTE = 1/ \varphi$

Efficient Frontier Interpretation

The DEA model constructs a piecewise linear efficiency frontier formed by the most efficient TPs. Those on the frontier receive phi (φ) value of 1 (fully efficient), while those below the frontier receive greater than 1, indicating the proportional increase in output needed to reach efficiency.

3.7.2 DEA Input–Output Variable Selection and Correlation Testing

The effectiveness of a DEA model depends critically on the appropriate selection of inputs and outputs. In this study, the goal was to identify variables that reflect both the operational investments made by training providers and the outcomes they are expected to deliver under government-sponsored short-term skill development schemes.

Initial Variables Considered

Based on data availability, policy relevance, and expert feedback, the following variables were initially considered:

- **Inputs:**

  1. Number of Trainees Enrolled

2. Average Experience of Trainers (in years)

3. Average Course Duration (in hours)

4. Average Training Cost per Trainee (in INR)

- **Outputs:**

1. Number of Trainees Certified

2. Number of Trainees Placed

Rationale for Variable Reduction: Correlation Testing

To avoid multicollinearity and improve the discriminatory power of the DEA model, a Pearson correlation analysis was conducted among all proposed inputs and outputs. The analysis revealed:

- A very high correlation between:
  - Certified Trainees and Placed Trainees ($r > 0.85$)
  - Course Duration and Average Training Cost ($r > 0.80$)

Table 3.1: Correlation between Input and Output Variables

	Number of Enrolled Trainees	**Average Experience of Trainers**	**Avg. Course Duration**	**Number of Trainees Certified**	**Number of Trainees Placed**
Number of Enrolled Trainees	1				
Average Experience of Trainers	-0.03820	1.00000			
Avg. Course Duration	-0.08192	0.01589	1.00000		

	Number of Enrolled Trainees	Average Experience of Trainers	Avg. Course Duration	Number of Trainees Certified	Number of Trainees Placed
Number of Trainees Certified	0.97883	-0.06154	-0.09832	1.00000	
Number of Trainees Placed	0.95572	-0.04219	-0.08532	0.96470	1.00000

In line with DEA best practices (Cooper, Seiford, & Tone, 2007), highly correlated variables were excluded to prevent redundancy and overfitting. The final variable set retained only those inputs and outputs that were empirically distinct and conceptually meaningful.

Final DEA Variable Set

- **Inputs:**
    1. Number of Trainees Enrolled
    2. Average Experience of Trainers
    3. Average Course Duration
- **Output:**
    - Number of Trainees Certified

This final set captures the scale of operations, human capital quality, and training intensity on the input side, and a certification outcome on the output side.

3.7.3 DEA Limitation and Interpretation

Although Data-Envelopment Analysis is well suited for benchmarking training-provider performance, its inherent limitations require cautious interpretation of the results:

- **Deterministic frontier**: All deviations from the frontier are treated as inefficiency; statistical noise or data errors are not separated from true performance gaps
- **Relative—not absolute—efficiency**: Efficiency scores are valid only against the West Bengal peer group analyzed here. A provider deemed efficient in this study could be inefficient when compared with a national or cross-state frontier.
- **Sensitivity to input–output selection:** Including or excluding highly correlated variables can inflate or deflate efficiency scores. This study mitigated dimensionality issues by retaining just three inputs and one output, but variable choice still influences results.
- **Small-sample and dimensionality effects:** With many inputs relative to DMUs, DEA may label an artificially high proportion of units as efficient. While our sample of 134 DMUs exceeds the 3 × (inputs + outputs) rule-of-thumb, some upward bias in efficiency scores cannot be ruled out.
- **Outlier influence:** Exceptional performers (or mis-reported values) can distort the frontier and thus the measured distance for all other units. Outlier checks were conducted, yet some residual influence may persist.
- **Orientation and scale assumptions:** An output-oriented, variable-returns-to-scale (VRS) model fits the policy focus on maximizing certifications under different provider sizes; however, results would differ under an input-oriented or CRS specification.

3.7.4 Second-Stage Tobit Regression – Purpose and Variables

Following DEA analysis, Tobit regression was employed to examine the relationship between contextual variables and efficiency scores. The Tobit model is methodologically appropriate for DEA applications because efficiency scores are bounded between 0 and 1, creating a censored dependent variable structure where ordinary least squares would yield biased estimates.

The application of censored regression models in DEA second-stage analysis is well-established in the literature. Hoff (2007) specifically address the importance of correctly specifying censored models when regressing DEA efficiency scores on environmental variables, noting that standard regression approaches can lead to inconsistent parameter estimates.

Why Tobit?

DEA scores (here also referred to as PTE score calculated as $1/\varphi$) are bounded between 0 and 1 (with 1 indicating full efficiency), which violates the assumptions of ordinary least squares (OLS) regression. The Tobit model, introduced by Tobin (1958), is designed to handle censored dependent variables, making it appropriate for analysing DEA results. It accommodates the fact that efficiency scores are:

- **Left-censored** at 0 (theoretical minimum)
- **Right-censored** at 1 (efficiency frontier)

Hence, it is particularly suited for modelling truncated outcomes like Partial Technical Efficiency cores.

Model Specification:

$\text{Partial Technical Efficiency}_i^* = \beta_0 + \beta_1 Z_{1i} + \beta_2 Z_{2i} + \ldots + \beta_k Z_{ki} + \varepsilon_i$

Where:

- $\text{Partial Technical Efficiency}_i^*$ is the latent efficiency score for training provider i
- Z_{ki} are environmental variables
- β_k are coefficients to be estimated
- $\varepsilon_i \sim N(0,\sigma^2)$ is the error term

The observed efficiency score E_i follows the censoring rule typical of bounded dependent variables.

Environmental Variables

Based on institutional theory and empirical precedents in educational efficiency research, the following variables were included:

- Percentage of female trainees (gender inclusivity indicator)
- Percentage of SC/ST/OBC trainees (social inclusion measure)

These variables capture institutional commitment to inclusive practices, which may influence operational efficiency through various channels including resource allocation, community engagement, and program design adaptations.

3.8 Qualitative Phase: Survey Design and Thematic Analysis

Following the DEA-based classification of training providers into efficiency tiers, a qualitative strand was undertaken to understand the operational practices, stakeholder experiences, and perceived institutional challenges underlying performance variations. This phase served to explain and contextualize the quantitative results, in alignment with the explanatory sequential mixed methods design.

3.8.1 Sampling Strategy for Qualitative Strand

A purposive stratified sampling approach was employed to select participants across the efficiency spectrum and provider types. Stratification ensured representation from both Industry-Integrated (II) and Center-Based (CB) training models, as well as across high performing ($PTE \geq 0.85$) and low performing ($PTE < 0.85$) categories.

The final qualitative sample included:

- 42 Training Providers (TPs) across all efficiency–type groups

- 113 Certified Trainees

This alignment between the quantitative DEA outcomes and qualitative sampling allowed for robust triangulation.

3.8.2 Survey Design and Administration

Two semi-structured survey instruments were developed:

1. **Training Provider Survey**: Focused on themes such as mobilization efforts, training delivery methods, infrastructure, placement linkages, and internal monitoring systems (refer appendix).

2. **Certified Trainee Survey**: Included Likert-scale items and open-ended prompts on training quality, trainer behaviour, infrastructure adequacy, satisfaction levels, and post-training expectations (refer appendix).

Surveys were administered via a mix of telephonic interviews, and online forms.

3.8.3 Thematic Analysis Framework

Qualitative responses were analysed using thematic analysis, following a structured coding approach:

- **Initial familiarization** with responses
- **Generation of open codes** linked to recurring patterns
- **Frequency mapping** across TP efficiency categories to detect contrasts

To ensure analytical rigor, both deductive (theory-informed) and inductive (data-driven) themes were allowed to emerge.

Key themes included:

- Mobilization Strategy
- Employer engagement and curriculum relevance
- Counselling practices and mobilization
- Placement follow-up and industry linkages
- Perceptions of quality, satisfaction, and inclusivity

3.8.4 Joint Displays and Integration

To facilitate integration, joint display matrices were created that aligned thematic codes with DEA performance tiers. For example:

- TPs with high efficiency often cited and proactive counselling
- Low-efficiency TPs frequently cited low motivation among candidates, infrastructure bottlenecks, and placement challenges

These matrices supported the meta-inference process by enabling side-by-side comparison and helping identify practice–performance linkages**.**

3.9 Population and Sampling

3.9.1. Population

The population for this study comprises all short-term skill training providers (TPs) delivering state government-sponsored programs in West Bengal during the years 2023 to 2025.

Although the larger registry of empanelled providers exceeds 1,200, not all were actively implementing training programs within the reference window. Based on administrative records from the Technical Education, Training & Skill Development (TET&SD) Department, approximately 570 TPs were both active and have had batches with certified candidates between April 2022 and March 2025. These 570 training institutions formed the defined population for the DEA-based benchmarking exercise.

3.9.2 Sampling Frame

The sampling frame consisted of these 570 active TPs, for whom verified contact details were available through TET&SD databases. Reaching out to each provider involved multiple rounds of telephonic calls, follow-up emails, and field visits. Data requests were standardized through a structured template shared in digital format.

3.9.3 Sampling Plan and Design

While a census approach was initially envisioned, operational realities necessitated a voluntary response sampling strategy. Several providers declined to share data, citing workload concerns or confidentiality issues, while others were unresponsive despite repeated follow-ups. In total, 134 TPs submitted complete, internally verified data suitable for DEA which was well above the minimum input DMU requirement to conduct DEA.

Efforts were made to ensure that the final dataset reflected diversity across:

- TP types (Industry-Integrated vs. Center-Based),
- Districts and geographies (urban, peri-urban, and rural)

3.9.4 Sample Size Justification

DEA literature recommends a minimum sample size of:

$$\text{DMUs} \geq 3\times \text{(Number of Inputs + Number of Outputs)}$$

(Cook, Zhu, & Emrouznejad, 1998). With three inputs and one output, this translates to a minimum of 12 DMUs.

With 134 TPs, the study's quantitative dataset significantly exceeds this threshold, ensuring:

- Adequate variation for efficiency differentiation,
- Statistical robustness in the DEA frontier construction,
- Reliable second-stage regression outcomes.

3.9.5 Data Collection

Quantitative data for DEA were collected over a seven-month period, using a standardized reporting template. Each participating TP submitted verified data on:

- Number of Trainees Enrolled
- Average Trainer Experience (in years)
- Average Course Duration (in hours)
- Number of Trainees Certified
- Number of Trainees Placed

In parallel, anonymized records of certified trainees was received from a few of the participating TPs. Sample of 233 certified trainees was generated using simple random sampling, of which 113 respondents (48%) completed the survey. These surveys captured experiences related to:

- Training quality and content delivery,
- Infrastructure availability,
- Trainer support and discipline,
- Job readiness

Qualitative survey questionnaire was also administered through google form to the 134 Training Providers whose efficiency scores were calculated using DEA, of which 42 TPs responded which was proportionate to the representation of TP type in the population.

3.9.6 Pilot Study

A pilot phase preceded full-scale data collection, involving:

- 10 Training Providers, and
- 15 Certified Trainees

This phase was critical to testing the clarity, reliability, and practical applicability of the research instruments. Based on feedback, the following refinements were made:

- The training provider survey was shortened, questions specific to funding challenges, support from Government was removed
- Certified Trainee Survey was shortened – questions pertaining to salary (pre and post training) was removed;
- Adjusted question flow for smoother navigation
- Enhanced outreach scripts for improved TP cooperation

This iterative refinement ensured greater instrument validity and alignment with mixed methods best practices (Creswell, 2014).

3.10 Data Analysis Tools

Given the study's mixed methods explanatory sequential design, different statistical and analytical tools were employed across the quantitative and qualitative phases. This section outlines the specific tools, platforms, and analytical procedures used to execute and interpret the data across all strands.

3.10.1 DEA Execution Using Excel Solver

The Data Envelopment Analysis was performed using Microsoft Excel in combination with the Solver Add-in, which enabled the formulation and solution of the linear programming models required for efficiency estimation.

Execution steps:

- A separate Solver model was created for each TP (DMU) to compute its output-oriented VRS efficiency score and CRS efficiency scores (to calculate Scale efficiency)
- The input and output data (as finalized in Section 3.7.2) were structured in matrix form.
- The model maximized the output scalar (ϕ) under VRS constraints, subject to the convexity condition ($\sum\lambda = 1$) (relaxed when calculating CRS score) and non-negativity.
- Peer weight (λ) variables were optimized within Solver to construct the best-practice frontier.

Solver output was then compiled to generate:

- **Pure Technical Efficiency (PTE)** – score generated post running output oriented VRS model
- **Scale Efficiency (SE)** using the ratio of CRS and VRS scores
- Value of **Lamda Weights** to identify the peers

Jackknife Sensitivity Test: Stability of DEA Results

To check how stable the DEA results were, a jackknife sensitivity test was carried out. This involved removing one training provider at a time and seeing if it made any real difference to the average efficiency scores. Using a one-sample t-test, the jackknife averages were compared with the original cluster averages. The results were clear—p-values of 1.0 in every case—showing that no single provider had the power to shift the overall efficiency outcome. In other words, the efficiency frontier is steady and not dependent on any one DMU, which makes the findings both reliable and robust.

3.10.2 Tobit Regression Modelling

To model the association between contextual characteristics and DEA-derived efficiency scores, Tobit regression was employed. The model was implemented using R statistical software, specifically the AER and censReg packages, which are capable of handling left- and right-censored dependent variables.

3.10.3 Thematic Analysis of Qualitative Data

The qualitative data — collected via structured and open-ended surveys from 42 training providers and 113 certified trainees — were analysed using manual coding and matrix-based thematic analysis.

Analytical procedures:

- Responses were first cleaned
- A coding framework was developed using a combination of deductive codes (based on the research question) and inductive codes (emerging from the data).
- Codes were grouped into themes such as:
  - Training delivery quality

- Mobilization and counselling
- Infrastructure and trainer capacity
- Placement support and employer engagement
- Trainee satisfaction and job readiness

Joint display matrices were created to map thematic occurrences against TP efficiency levels (e.g., High Performing vs. Low Performing) and TP type (Industry-Integrated vs. Center-Based). This enabled triangulation and the generation of meta-inferences, as outlined in Section 3.6.2.

While no software (e.g., NVivo) was used, the structured matrix-based approach ensured transparency, reliability, and analytical rigor.

3.11 Ethical Considerations

This study adhered to high ethical standards throughout all stages of the research process, especially in the design and administration of data collection tools involving human participants. As the research involved gathering both organizational and individual-level data, ethical safeguards were implemented across both quantitative and qualitative components.

Informed Consent

All participating training providers (TPs) and certified trainees were informed of:

- The purpose of the study
- The voluntary nature of their participation
- Their right to withdraw at any time

- The anonymity and confidentiality of their responses

Verbal consent was reaffirmed for responses collected through telephonic interviews.

Anonymity and Confidentiality

All quantitative data from TPs were anonymized before analysis. Identifiers such as TP name, district were coded to protect institutional identity. In the case of certified trainees, names and contact information were not collected beyond what was necessary for one-time outreach.

Data were securely stored in encrypted digital files, and only the researcher had access to identifiable information during the collection phase. For reporting purposes, all findings were presented in aggregated form, ensuring no participant could be individually identified.

Voluntary Participation

Participation in both the TP and trainee surveys was entirely voluntary. No incentives were offered, and no penalties were applied for non-participation. The researcher maintained a neutral and non-coercive stance during all engagements.

3.12 Limitations of the Methodology

While the study employed a robust mixed methods framework and adhered to rigorous data validation standards, certain limitations are acknowledged. These do not undermine the findings but provide context for interpreting results and framing future research directions.

1. Voluntary Response Bias in Quantitative Sampling

Despite efforts to conduct a census of all active training providers, data were obtained from only 134 out of 570 institutions. The reliance on a voluntary response sample introduces potential self-selection bias—providers with better systems or stronger performance may have been more willing to share data. While the sample retained geographic and institutional diversity, the findings may not fully represent the characteristics of non-responding TPs.

2. Contextual Data Constraints in Regression Analysis

The Tobit regression included demographic indicators such as gender and caste composition. However, other potentially influential variables—such as socio-economic status of the trainees, trainer-to-trainee ratios, trainee's academic background, etc. were unavailable and thus excluded.

3. Limitations of Self-Reported Qualitative Data

The qualitative findings are based on self-reported surveys from training providers and certified trainees. Responses may be subject to recall bias, social desirability, or selective disclosure. Moreover, while thematic saturation was achieved, the insights represent perceived—not objectively verified—experiences.

4. Absence of Longitudinal Tracking

Given the cross-sectional design, the study does not assess changes in efficiency over time or track long-term outcomes such as sustained employment or income mobility. Such longitudinal tracking would enhance the understanding of training program impact.

While these limitations frame the boundary conditions of the study, they also open avenues for future research—especially those incorporating longitudinal datasets.

3.13 Summary

This chapter detailed the research methodology adopted to evaluate the comparative efficiency of short-term skill training providers in West Bengal using a mixed methods approach. Anchored in an explanatory sequential design, the study combined quantitative benchmarking through output-oriented DEA with qualitative insights from training providers and certified trainees.

The quantitative phase involved the development of a DEA model using three carefully selected inputs and one output, applied to 134 TPs. A second-stage Tobit regression was conducted to examine the influence of contextual variables such as trainee demographics and institutional type on efficiency scores.

The qualitative phase, guided by the DEA results, employed stratified purposive sampling to collect experiential data from both TPs and trainees. These narratives were thematically analysed and integrated with the quantitative findings through meta-inference and joint display techniques.

Methodological choices regarding sample size, data collection procedures, and analytical tools—including Excel Solver, R, and manual coding—were explained in detail. Ethical safeguards and a pilot study were also implemented to ensure validity and data integrity.

The next chapter presents the quantitative results of the DEA and regression analysis, Qualitative analysis of TP and Trainee responses, followed by results and discussion in Chapter 5.

CHAPTER 4: DATA ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter presents a detailed analysis and interpretation of the data gathered through the mixed-methods approach described in Chapter 3. The structure of the analysis is designed to align closely with the study's research objectives. It begins with a quantitative assessment using Data Envelopment Analysis to identify efficiency patterns among training providers, and then moves into qualitative insights drawn from interviews with both providers and certified trainees. By combining these two strands of analysis, the chapter offers a well-rounded perspective on the performance of skill training providers in West Bengal.

The chapter is divided into three core sections. Section 4.2 covers the quantitative findings, including descriptive statistics, K-means clustering outcomes, DEA efficiency scores, and the results of Tobit regression analysis. Section 4.3 explores the qualitative dimensions of the study, presenting thematic insights from the perspectives of training providers and trainees. Finally, Section 4.4 brings together both the quantitative and qualitative findings, weaving them into an integrated analysis that informs the broader conclusions and recommendations of the study.

4.2 Quantitative Analysis: Data Envelopment Analysis

4.2.1 Descriptive Statistics of DEA Inputs and Outputs

The dataset comprises 134 short-term skill training providers operating under various government schemes in West Bengal. The descriptive statistics for the DEA input and output variables reveal significant heterogeneity among training providers. This section presents the summary statistics for the input and output variables used in the DEA model. These include:

- **Number of Enrolled Trainees**
- **Average Experience of Trainers**
- **Average Course Duration**
- **Number of Trainees Certified**

Summary statistics for inputs and output variables are presented below:

Table 4.1: Summary Statistics of DEA Inputs and Output Variables

Variable	Mean	Std Dev	Min	Max
Input 1: Enrolled Trainees	430.13	538.71	25	3339
Input 2: Average Trainer Experience (years)	5.39	2.78	1.33	20
Input 3: Course Duration (hours)	400.77	81.75	100	733.33
Output 1: Certified Trainees	354.61	442.58	11	2949

Interpretation

The data reveal considerable variability across both input and output indicators, as reflected in the high standard deviations relative to their respective means. The broad range—from minimum to maximum values—underscores the diversity among training providers. Notably, the mean values for all variables are higher than their medians, pointing to right-skewed distributions. This skew is especially evident in trainee numbers (both enrolled and certified), suggesting that while most providers operate on a smaller scale, a few large institutions account for a disproportionately high share of the total figures.

Trainer experience varies widely—ranging from 1.3 to 20 years—highlighting differences in organizational models and sectoral specializations. Similarly, course durations span a broad spectrum, further reinforcing the heterogeneity within the dataset. This diversity across key variables provided a strong rationale for implementing a clustering approach prior to conducting the DEA, to ensure meaningful efficiency comparisons within homogeneous groups.

4.2.2 Clustering of DMUs

To account for the heterogeneity among the 134 training providers, a K-means clustering analysis was performed using the three DEA input variables: number of enrolled trainees, average trainer experience, and average course duration. The optimal number of clusters was identified through the elbow method, which balances model simplicity with explanatory power.

Clustering Methodology

- **Variables used**: Number of enrolled trainees, average trainer experience, and average course duration
- **Tool**: Excel Solver
- **Technique**: Elbow method was used to determine the optimal number of clusters by plotting total within-cluster distance against varying values of *k*.
- **Result**: The decision on the optimal number of clusters was informed by both the elbow method—which indicated a suitable range between $k = 3$ and $k = 4$—and established best practices in Data Envelopment Analysis. While clustering with $k = 4$ produced a solution, one of the resulting clusters contained only eight Decision Making Units (DMUs), raising concerns about its adequacy. According to the guideline proposed by Banker, Charnes, and Cooper (1984), the number of DMUs should be at least three times the total number of input and output variables. This ensures meaningful discrimination among units and reduces the likelihood of overestimating efficiency due to limited peer comparisons. In line with this criterion and to uphold methodological rigor, the analysis proceeded with $k = 3$ clusters. (Banker, Charnes, & Cooper, 1984).

Each DMU was assigned to a cluster based on proximity to the cluster centroid using Euclidean distance.

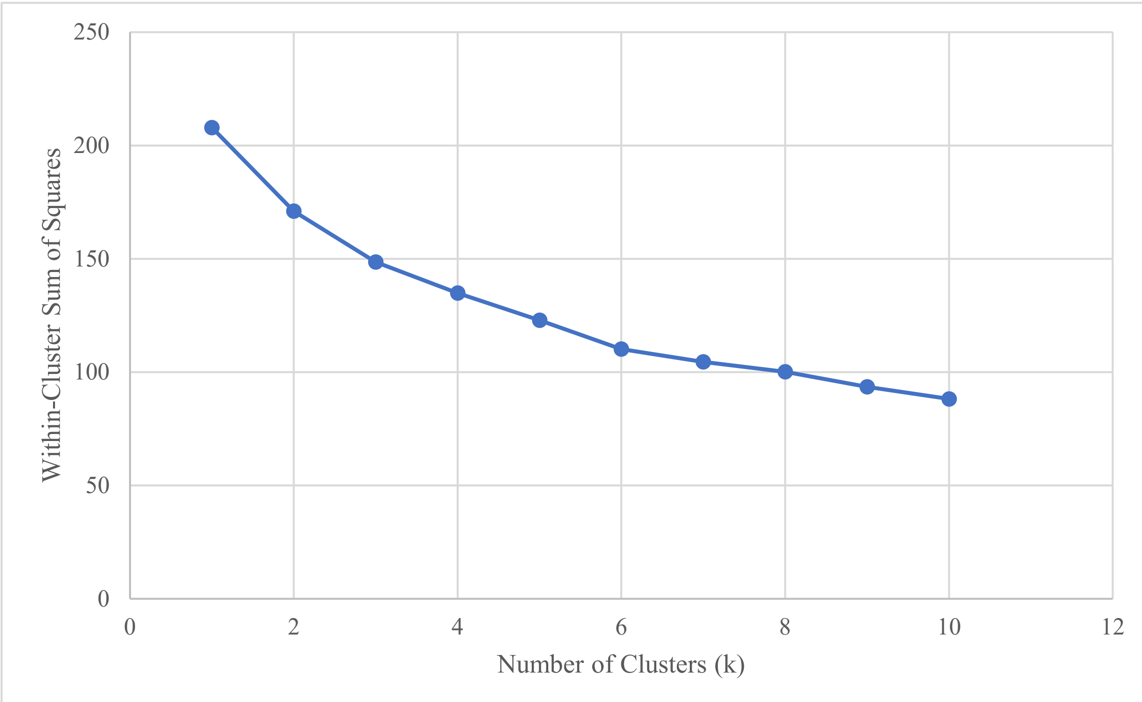

Figure 4.1: Elbow-Method for K-Means Clustering

Cluster Profiles

- **Cluster 1**: Large-scale providers, Enrolled Trainees (Average ~1170 candidates) moderate trainer experience, shorter courses
- **Cluster 2**: Smaller enrolment, highly experienced trainers (average ~8 years), longer courses
- **Cluster 3**: Small–moderate enrolment, least experienced trainers, longest courses (Average ~ 414 hours)

Table 4.2: Cluster-Wise Summary

Metric	Cluster 1	Cluster 2	Cluster 3
DMU Count	31	42	61
Input 1: Enrolled Trainees	**1169.87**	188.52	220.56
Input 2: Average Trainer Experience (years)	5.32	**8.03**	3.61

Metric	Cluster 1	Cluster 2	Cluster 3
Input 3: Course Duration (hours)	371.33	403.34	**413.97**
Output 1: Certified Trainees	943.32	151.79	195.08

4.2.2 Technical Efficiency Score Analysis

This section presents the findings from the technical efficiency analysis of 134 skill training providers (Decision Making Units, or DMUs) in West Bengal, conducted using the Data Envelopment Analysis framework. To account for the diversity in operational settings and objectives, the study applied both cluster-specific and global DEA models, allowing for a more nuanced understanding of provider performance.

Cluster-Based and Global DEA Approaches

Recognizing the varied nature of training institutions, a two-tiered approach was adopted:

- **Cluster-Level DEA**

Training providers were first categorized into three distinct groups—Cluster 1 (31 DMUs), Cluster 2 (42 DMUs), and Cluster 3 (61 DMUs)—based on similarities in their operational features and input-output configurations, as detailed in Section 3.6.4. Separate DEA models were then run for each cluster, establishing efficiency frontiers tailored to each group. This allowed for fairer benchmarking by comparing providers operating under comparable conditions. The results of the Pure Technical Score and Scale Efficiency Score calculated using DEA Output-Oriented VRS Model is presented below in Table 4.3.

Table 4.3: Cluster 1 Pure Technical Efficiency Scores and Scale Efficiency Score

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 1_1	Industry-Integrated TPs	2256	9.4	343	1944	0.9517	0.9992
Cluster 1_2	Industry-Integrated TPs	870	6.3	325	593	0.7232	0.9959
Cluster 1_3	Industry-Integrated TPs	840	5.5	396	810	1.0000	1.0000
Cluster 1_4	Industry-Integrated TPs	1570	3.8	396	1000	0.6956	0.9986
Cluster 1_5	Industry-Integrated TPs	630	3.3	303	590	1.0000	0.9863
Cluster 1_6	Industry-Integrated TPs	774	6.7	381	648	0.8661	0.9990
Cluster 1_7	Industry-Integrated TPs	1080	4.4	254	890	0.9005	0.9932
Cluster 1_8	Industry-Integrated TPs	678	4.4	255	508	0.8074	0.9800
Cluster 1_9	Industry-Integrated TPs	796	5.8	367	751	0.9824	0.9979
Cluster 1_10	Industry-Integrated TPs	1002	3.3	409	736	0.8005	0.9903
Cluster 1_11	Industry-Integrated TPs	696	7.2	390	681	1.0000	1.0000
Cluster 1_12	Industry-Integrated TPs	1092	7.7	412	941	0.9129	0.9967

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 1_13	Industry-Integrated TPs	763	4.3	260	711	1.0000	0.9908
Cluster 1_14	Industry-Integrated TPs	660	6.7	419	621	0.9836	0.9788
Cluster 1_15	Industry-Integrated TPs	1131	7.3	420	300	0.2817	0.9953
Cluster 1_16	Industry-Integrated TPs	654	5.1	100	578	1.0000	0.9752
Cluster 1_17	Center Based TPs	642	6.0	386	600	0.9892	0.9692
Cluster 1_18	Center Based TPs	622	5.0	390	520	1.0000	0.8623
Cluster 1_19	Center Based TPs	762	6.7	476	611	0.8255	0.9987
Cluster 1_20	Center Based TPs	2552	3.6	374	2310	1.0000	1.0000
Cluster 1_21	Center Based TPs	2814	7.0	504	1852	0.7341	0.9840
Cluster 1_22	Center Based TPs	1156	2.6	390	1030	1.0000	0.9744
Cluster 1_23	Center Based TPs	1204	6.7	391	730	0.6467	1.0000
Cluster 1_24	Center Based TPs	784	3.8	392	736	1.0000	0.9944
Cluster 1_25	Center Based TPs	920	4.5	390	752	0.8675	0.9974
Cluster 1_26	Center Based TPs	1041	4.8	390	847	0.8652	0.9987
Cluster 1_27	Center Based TPs	972	6.7	390	852	0.9214	0.9998

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 1_28	Center Based TPs	1716	3.7	390	1468	0.9377	0.9987
Cluster 1_29	Center Based TPs	1269	5.2	428	949	0.8003	0.9988
Cluster 1_30	Center Based TPs	981	4.5	390	735	0.7976	0.9978
Cluster 1_31	Center Based TPs	3339	3.1	398	2949	1.0000	1.0000

Table 4.4: Cluster 2 Pure Technical Efficiency Scores and Scale Efficiency Score

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 2_1	Industry - Integrated TPs	178	7.8	330	133	0.7714	0.9686
Cluster 2_2	Industry - Integrated TPs	32	12.0	390	21	0.7308	0.8980
Cluster 2_3	Industry - Integrated TPs	72	10.0	390	72	1.0000	1.0000
Cluster 2_4	Industry - Integrated TPs	240	10.0	295	212	1.0000	0.9245
Cluster 2_5	Industry - Integrated TPs	492	6.6	397	441	1.0000	1.0000
Cluster 2_6	Industry -	138	6.3	503	121	0.8768	1.0000

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
	Integrated TPs						
Cluster 2_7	Industry - Integrated TPs	105	5.3	390	84	1.0000	0.8000
Cluster 2_8	Industry - Integrated TPs	537	6.6	438	273	0.5971	0.9653
Cluster 2_9	Industry - Integrated TPs	25	11.0	240	21	1.0000	0.8400
Cluster 2_10	Industry - Integrated TPs	72	5.6	390	64	0.9971	0.8915
Cluster 2_11	Industry - Integrated TPs	150	7.0	370	135	0.9024	0.9973
Cluster 2_12	Industry - Integrated TPs	180	6.7	390	179	0.9944	1.0000
Cluster 2_13	Industry - Integrated TPs	96	9.0	390	75	0.7813	1.0000
Cluster 2_14	Industry - Integrated TPs	180	7.2	665	162	0.9000	1.0000
Cluster 2_15	Industry - Integrated TPs	60	6.7	340	59	1.0000	0.9833

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 2_16	Industry - Integrated TPs	230	5.9	455	192	0.8686	0.9759
Cluster 2_17	Industry - Integrated TPs	132	7.1	405	126	0.9545	1.0000
Cluster 2_18	Industry - Integrated TPs	72	6.5	390	72	1.0000	1.0000
Cluster 2_19	Industry - Integrated TPs	30	11.0	650	23	0.8671	0.8842
Cluster 2_20	Industry - Integrated TPs	300	9.3	628	214	0.7384	0.9660
Cluster 2_21	Industry - Integrated TPs	86	7.6	390	59	0.6860	1.0000
Cluster 2_22	Industry - Integrated TPs	25	5.7	224	11	1.0000	0.4400
Cluster 2_23	Industry - Integrated TPs	210	6.1	453	165	0.7999	0.9822
Cluster 2_24	Center Based TPs	55	7.3	340	35	0.6527	0.9750
Cluster 2_25	Center Based TPs	252	7.0	390	252	1.0000	1.0000

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 2_26	Center Based TPs	124	5.8	390	97	0.7823	1.0000
Cluster 2_27	Center Based TPs	529	16.4	374	426	0.9353	0.9858
Cluster 2_28	Center Based TPs	588	7.5	392	508	1.0000	1.0000
Cluster 2_29	Center Based TPs	179	5.5	390	48	0.2763	0.9705
Cluster 2_30	Center Based TPs	177	9.4	390	152	0.8588	1.0000
Cluster 2_31	Center Based TPs	300	8.4	502	224	0.7729	0.9660
Cluster 2_32	Center Based TPs	190	6.7	390	173	0.9105	1.0000
Cluster 2_33	Center Based TPs	451	5.5	379	401	1.0000	1.0000
Cluster 2_34	Center Based TPs	140	5.4	390	140	1.0000	1.0000
Cluster 2_35	Center Based TPs	30	6.8	400	12	0.5775	0.6926
Cluster 2_36	Center Based TPs	342	5.6	390	253	0.8124	0.9905
Cluster 2_37	Center Based TPs	231	5.8	337	166	0.7913	0.9267

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 2_38	Center Based TPs	78	5.5	390	57	0.8703	0.8397
Cluster 2_39	Center Based TPs	44	6.5	390	42	1.0000	0.9545
Cluster 2_40	Center Based TPs	156	13.2	408	125	0.8013	1.0000
Cluster 2_41	Center Based TPs	354	12.2	396	305	0.9178	0.9986
Cluster 2_42	Center Based TPs	56	20.0	390	45	0.8203	0.9796

Cluster 3

Table 4.5: Cluster 3 Pure Technical Efficiency Scores and Scale Efficiency Score

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 3_1	Industry-Integrated TPs	30	3.0	400	27	1.0000	0.9000
Cluster 3_2	Industry-Integrated TPs	492	2.7	346	362	1.0000	0.7391
Cluster 3_3	Industry-Integrated TPs	90	4.7	400	87	0.9807	0.9857
Cluster 3_4	Industry-Integrated TPs	60	2.0	650	54	0.9500	0.9474

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 3_5	Industry-Integrated TPs	252	4.3	390	248	0.9858	0.9997
Cluster 3_6	Industry-Integrated TPs	132	2.1	330	69	1.0000	0.5235
Cluster 3_7	Industry-Integrated TPs	60	5.0	650	37	0.6379	0.9667
Cluster 3_8	Industry-Integrated TPs	480	4.5	452	464	0.9689	0.9998
Cluster 3_9	Industry-Integrated TPs	60	2.0	375	54	0.9650	0.9327
Cluster 3_10	Industry-Integrated TPs	600	2.6	409	597	1.0000	1.0000
Cluster 3_11	Industry-Integrated TPs	90	4.3	650	88	0.9919	0.9857
Cluster 3_12	Industry-Integrated TPs	72	3.0	390	37	0.5306	0.9684
Cluster 3_13	Industry-Integrated TPs	570	2.0	461	567	1.0000	1.0000
Cluster 3_14	Industry-Integrated TPs	280	2.9	328	270	1.0000	0.9662
Cluster 3_15	Industry-Integrated TPs	36	5.0	390	17	0.5120	0.9222
Cluster 3_16	Industry-Integrated TPs	25	5.0	500	16	1.0000	0.6400

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 3_17	Industry-Integrated TPs	60	2.0	420	54	0.9500	0.9474
Cluster 3_18	Industry-Integrated TPs	204	3.0	400	185	0.9155	0.9921
Cluster 3_19	Industry-Integrated TPs	36	1.3	390	32	1.0000	0.8889
Cluster 3_20	Industry-Integrated TPs	288	2.0	390	275	0.9741	0.9833
Cluster 3_21	Industry-Integrated TPs	272	3.3	398	269	0.9952	0.9955
Cluster 3_22	Industry-Integrated TPs	180	3.4	733	176	0.9849	0.9939
Cluster 3_23	Industry-Integrated TPs	420	4.0	382	401	0.9583	0.9984
Cluster 3_24	Industry-Integrated TPs	396	5.2	390	383	0.9690	1.0000
Cluster 3_25	Industry-Integrated TPs	90	4.0	300	75	1.0000	0.8333
Cluster 3_26	Industry-Integrated TPs	170	4.5	555	168	0.9887	1.0000
Cluster 3_27	Industry-Integrated TPs	65	3.0	360	53	0.8513	0.9578
Cluster 3_28	Industry-Integrated TPs	60	4.0	340	58	1.0000	0.9667

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 3_29	Industry-Integrated TPs	144	4.5	390	144	1.0000	1.0000
Cluster 3_30	Industry-Integrated TPs	150	5.2	362	122	0.8203	0.9918
Cluster 3_31	Industry-Integrated TPs	162	4.0	482	154	0.9543	0.9968
Cluster 3_32	Industry-Integrated TPs	66	3.0	390	50	0.7859	0.9639
Cluster 3_33	Center Based TPs	131	3.4	390	113	0.8723	0.9894
Cluster 3_34	Center Based TPs	178	5.2	390	170	0.9556	1.0000
Cluster 3_35	Center Based TPs	248	2.7	390	189	0.7698	0.9919
Cluster 3_36	Center Based TPs	393	3.9	390	323	0.8242	0.9992
Cluster 3_37	Center Based TPs	163	4.8	426	116	0.7119	0.9998
Cluster 3_38	Center Based TPs	60	4.8	390	21	0.3621	0.9667
Cluster 3_39	Center Based TPs	243	3.3	390	219	0.9074	0.9948
Cluster 3_40	Center Based TPs	210	2.1	390	154	0.7449	0.9864
Cluster 3_41	Center Based TPs	486	3.2	383	460	0.9551	0.9944
Cluster 3_42	Center Based TPs	252	4.9	484	220	0.8742	0.9998
Cluster 3_43	Center Based TPs	72	3.0	390	44	0.6310	0.9684
Cluster 3_44	Center Based TPs	628	3.3	364	523	1.0000	0.9841

DMU Number	DMU Type	(I) Number of Enrolled Trainees	(I) Average Experience of Trainers	(I) Avg. Course Duration	(O) Number of Trainees Certified	PTE	Scale Efficiency
Cluster 3_45	Center Based TPs	278	4.8	384	253	0.9123	0.9990
Cluster 3_46	Center Based TPs	240	4.5	390	216	0.9011	1.0000
Cluster 3_47	Center Based TPs	243	2.5	473	224	0.9313	0.9918
Cluster 3_48	Center Based TPs	264	3.6	390	239	0.9101	0.9964
Cluster 3_49	Center Based TPs	210	2.1	390	186	0.8997	0.9864
Cluster 3_50	Center Based TPs	65	2.8	353	48	0.8065	0.9156
Cluster 3_51	Center Based TPs	133	4.5	390	117	0.8814	0.9980
Cluster 3_52	Center Based TPs	150	2.9	394	104	0.7032	0.9871
Cluster 3_53	Center Based TPs	400	4.8	390	388	0.9719	1.0000
Cluster 3_54	Center Based TPs	240	4.7	390	121	0.5048	1.0000
Cluster 3_55	Center Based TPs	573	3.3	390	480	0.8786	0.9585
Cluster 3_56	Center Based TPs	110	3.7	390	101	0.9279	0.9895
Cluster 3_57	Center Based TPs	198	3.3	390	145	0.7383	0.9933
Cluster 3_58	Center Based TPs	474	4.1	390	473	1.0000	1.0000
Cluster 3_59	Center Based TPs	108	4.6	390	106	0.9893	0.9921
Cluster 3_60	Center Based TPs	216	4.0	390	187	0.8687	0.9977
Cluster 3_61	Center Based TPs	396	4.3	390	367	0.9286	1.0000

Global DEA

Alongside the cluster-level assessment, a global DEA model was also applied to the entire dataset of 134 DMUs. This model constructed a single efficiency frontier spanning all providers, enabling comparisons on a broader scale. The global analysis helps identify standout performers across the full landscape and supports strategic insights that can inform state-level planning and policy.

Together, these two lenses—cluster-specific and global—offer a balanced perspective: one that respects contextual differences while also striving for consistent benchmarks. Importantly, the total number of DMUs far exceeded the recommended minimum (three times the number of input and output variables, per Banker, Charnes, & Cooper, 1984), ensuring the statistical reliability and discriminatory power of the results.

Descriptive Statistics of Pure Technical Efficiency (PTE) and Scale Efficiency (SE) Scores

Table 4.6 provides a summary of the Pure Technical Efficiency (PTE) and Scale Efficiency (SE) scores calculated for each cluster as well as for the overall DEA model. The table reports key descriptive statistics, including the mean, standard deviation, median, minimum and maximum values, as well as measures of distribution such as skewness, kurtosis, and the first (Q1) and third quartiles (Q3), offering a comprehensive snapshot of efficiency across providers.

Table 4.6: Descriptive Statistics of PTE

Cluster/All	No. of DMUs (N)	Score	Mean	SD	Median	Min	Max	Skewness	Kurtosis	Q1	Q3
Cluster 1	31	PTE	0.8804	0.1538	0.9214	0.2817	1	-2.0644	8.3950	0.8040	1.0000
		SE	0.9888	0.0251	0.9974	0.8623	1	-4.3276	22.2561	0.9883	0.9989
Cluster 2	42	PTE	0.8630	0.1525	0.8884	0.2763	1	-1.5809	6.4329	0.7845	1.0000
		SE	0.9475	0.1036	0.9846	0.4400	1	-3.3382	15.4856	0.9572	1.0000

Cluster/All	No. of DMUs (N)	Score	Mean	SD	Median	Min	Max	Skewness	Kurtosis	Q1	Q3
Cluster 3	61	PTE	0.8858	0.1456	0.9500	0.3621	1	-1.7246	5.5222	0.8513	0.9893
		SE	0.9618	0.0839	0.9918	0.5235	1	-3.6946	17.2516	0.9667	0.9992
Global Total	134	PTE	0.8592	0.1503	0.9003	0.2682	1	-1.6424	6.1235	0.7867	0.9750
		SE	0.9755	0.0732	0.9964	0.4400	1	-5.5323	36.1240	0.9851	0.9999

Note: All values are rounded to four decimal places

Interpretation of Technical and Scale Efficiency

The mean Pure Technical Efficiency (PTE) scores indicate a moderate level of efficiency across the clusters, ranging from approximately 0.86 in Cluster 2 to 0.89 in Cluster 3. These values suggest that many training providers are operating below the optimal frontier in terms of converting inputs into certified trainees. In contrast, Scale Efficiency (SE) scores are notably higher. Cluster 1, in particular, stands out with a mean SE of 0.989 and a low standard deviation of 0.025, suggesting that most providers in this group are functioning close to their most productive scale size, with minimal variation.

The distribution of efficiency scores, as reflected in the skewness values, leans consistently negative. This pattern indicates that a large number of DMUs have scores clustering near the efficiency frontier (value of 1), a common trait in DEA studies. Additionally, the elevated kurtosis—especially pronounced in Cluster 1 (22.26) and the global results (36.12)—reveals heavy-tailed distributions. This points to the presence of a few providers whose scale efficiencies deviate substantially from the norm, potentially marking them as outliers.

A closer look at the interquartile ranges reveals that variability in efficiency scores differs across clusters. Cluster 1 again demonstrates the narrowest spread in SE, reflecting a relatively homogeneous group with consistently strong scale performance. In contrast, Cluster 2 displays a broader distribution of scores, suggesting greater diversity in operational scale and highlighting opportunities for targeted performance improvements among certain providers in that cluster.

Importance of Global DEA Evaluation

While cluster-specific DEA models are essential for benchmarking providers within similar operational contexts, the global DEA results serve a different but equally critical purpose. By establishing a single, unified efficiency frontier for all 134 DMUs, the global model enables a broader performance comparison—one that identifies truly outstanding providers that set standards across the entire system, not just within their respective clusters.

This broader reference set also enhances the discriminatory power of the analysis, reducing the risk of inflated efficiency scores that can occur when comparisons are confined to narrower peer groups. Furthermore, the global DEA model adheres to established methodological standards (as per Banker et al., 1984), with the number of DMUs comfortably exceeding the recommended minimum of three times the number of input and output variables. This ensures statistical robustness and meaningful benchmarking.

From a policy perspective, the global scores are particularly valuable. They equip decision-makers with a comprehensive view of system-wide performance, allowing for the identification of top-performing providers and the strategic targeting of support where it is most needed. In doing so, global DEA results support more informed planning, smarter resource allocation, and the replication of best practices across the broader skill training ecosystem.

Cluster and Global DEA Frontiers

Cluster 1

The below graphs illustrate the efficiency frontier for Cluster 1, capturing the relationship between the inputs and the number successfully certified. DMUs that lie directly on the frontier represent efficient performers (with efficiency scores of 1.0), serving as benchmarks within this cluster. Notably, out of the 31 DMUs in Cluster 1, 10 training providers achieved a Pure Technical Efficiency (PTE) score of 1.0 (Refer table 4.7), of which 5 are II and 5 are CB. In contrast, DMUs positioned below the frontier are relatively inefficient, indicating potential areas where input-to-output conversion could be improved.

Table 4.7: List of Efficient DMUs in Cluster 1

DMU Number	DMU Type	PTE	Scale Efficiency
Cluster 1_3	Industry-Integrated TPs	1	1
Cluster 1_5	Industry-Integrated TPs	1	0.9863
Cluster 1_11	Industry-Integrated TPs	1	1
Cluster 1_13	Industry-Integrated TPs	1	0.9908
Cluster 1_16	Industry-Integrated TPs	1	0.9752
Cluster 1_18	Center Based TPs	1	0.8623
Cluster 1_20	Center Based TPs	1	1
Cluster 1_22	Center Based TPs	1	0.9744
Cluster 1_24	Center Based TPs	1	0.9944
Cluster 1_31	Center Based TPs	1	1

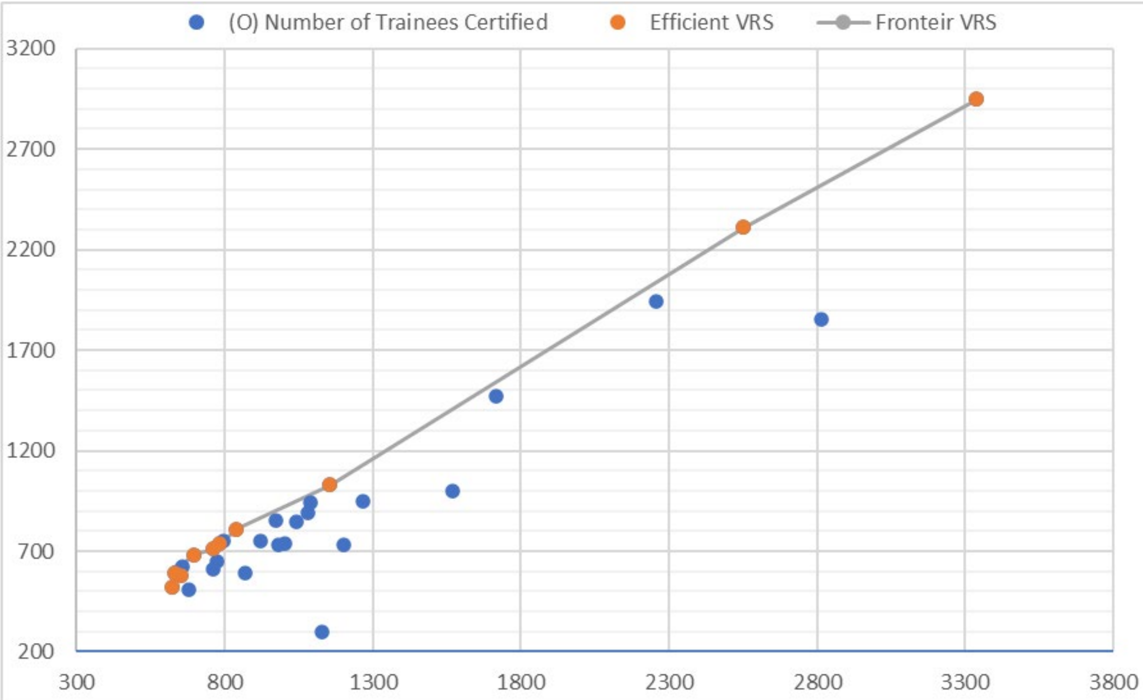

Figure 4.2: Cluster 1 Efficiency Frontier — Input 1 (Enrolled Trainees) vs. Output (Certified Trainees)

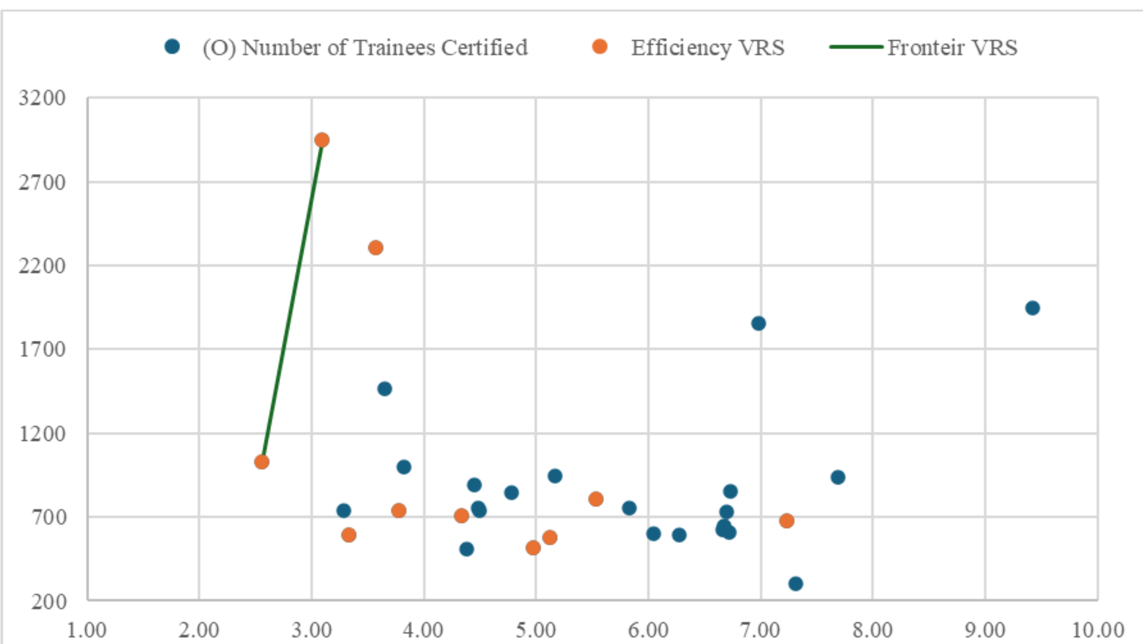

Figure 4.3: Cluster 1 Efficiency Frontier — Input 2 (Trainer Experience) vs. Output (Certified Trainees)

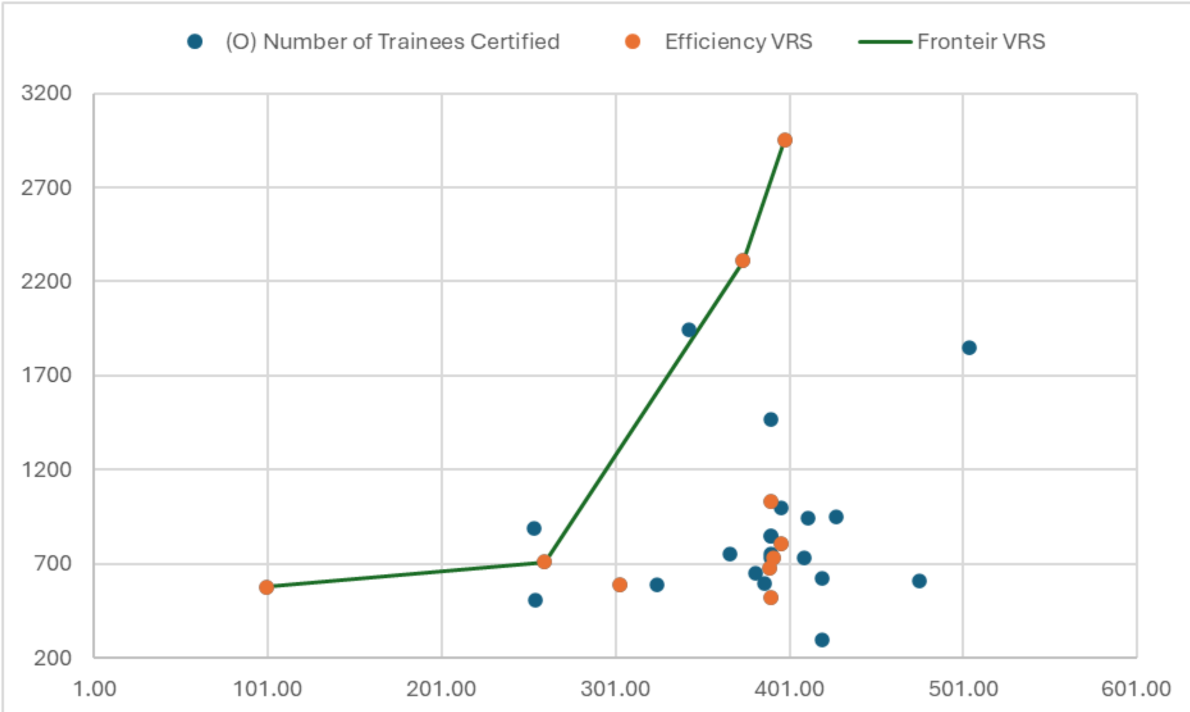

Figure 4.4: Cluster 1 Efficiency Frontier — Input 3 (Course Duration vs. Output (Certified Trainees)

Cluster 2

The graphs below present the efficiency frontier for Cluster 2, illustrating how effectively the 42 training providers in this group convert operational inputs into certified outputs. DMUs positioned on the frontier are considered technically efficient within the cluster, each achieving a Pure Technical Efficiency (PTE) score of 1.0. These providers represent best-practice performers and serve as reference points for their peers.

In this cluster, 13 DMUs (8 II and 5 CB) achieved full technical efficiency, accounting for just under one-third of the total. This proportion reflects a notable performance standard within the group—one that sets a clear benchmark for others to aim toward. Conversely, DMUs that fall below the efficiency frontier are relatively less efficient. These providers stand to benefit from closer analysis of their more efficient counterparts, particularly in terms of operational practices and resource utilization, to strengthen their input-to-output conversion and move closer to the efficiency frontier.

Table 4.8: List of Efficient DMUs in Cluster 2

DMU Number	DMU Type	PTE	Scale Efficiency
Cluster 2_3	Industry-Integrated TP	1.0000	1.0000
Cluster 2_4	Industry-Integrated TP	1.0000	0.9245
Cluster 2_5	Industry-Integrated TP	1.0000	1.0000
Cluster 2_7	Industry-Integrated TP	1.0000	0.8000
Cluster 2_9	Industry-Integrated TP	1.0000	0.8400
Cluster 2_15	Industry-Integrated TP	1.0000	0.9833
Cluster 2_18	Industry-Integrated TP	1.0000	1.0000
Cluster 2_22	Industry-Integrated TP	1.0000	0.4400
Cluster 2_25	Center Based TP	1.0000	1.0000
Cluster 2_28	Center Based TP	1.0000	1.0000
Cluster 2_33	Center Based TP	1.0000	1.0000
Cluster 2_34	Center Based TP	1.0000	1.0000
Cluster 2_39	Center Based TP	1.0000	0.9545

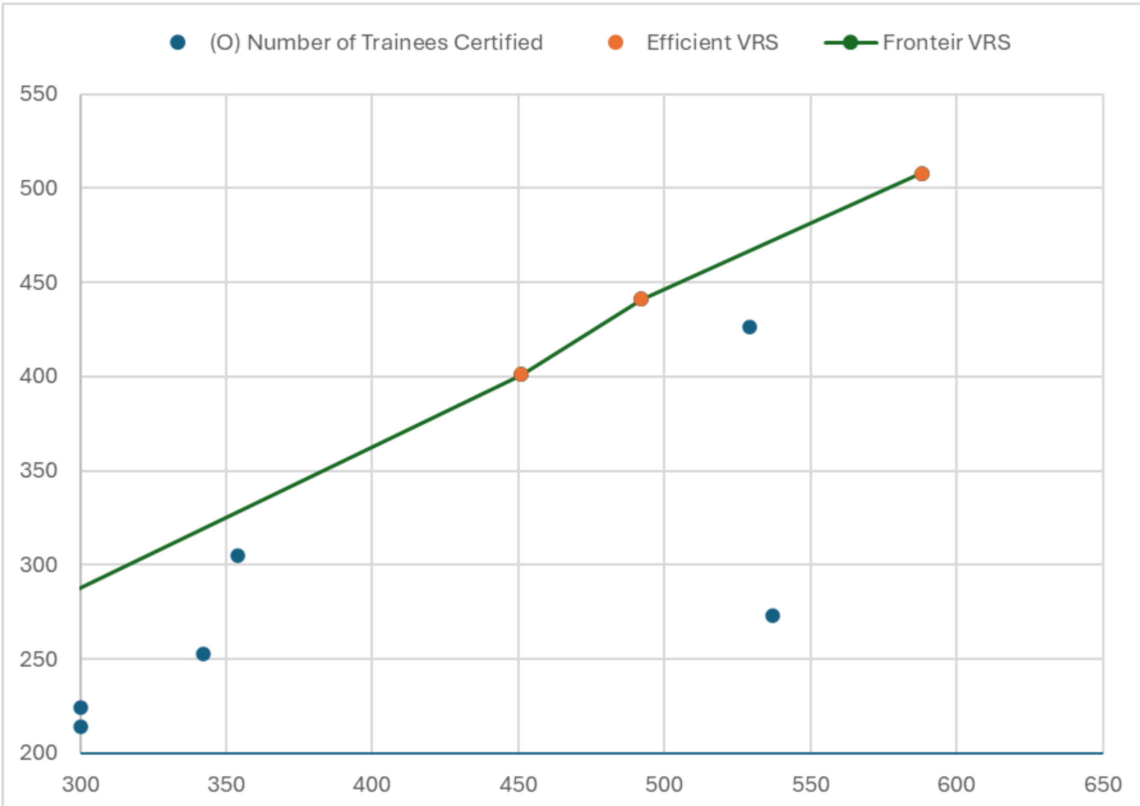

Figure 4.5: Cluster 2 Efficiency Frontier — Input 1 (Enrolled Trainees) vs. Output (Certified Trainees)

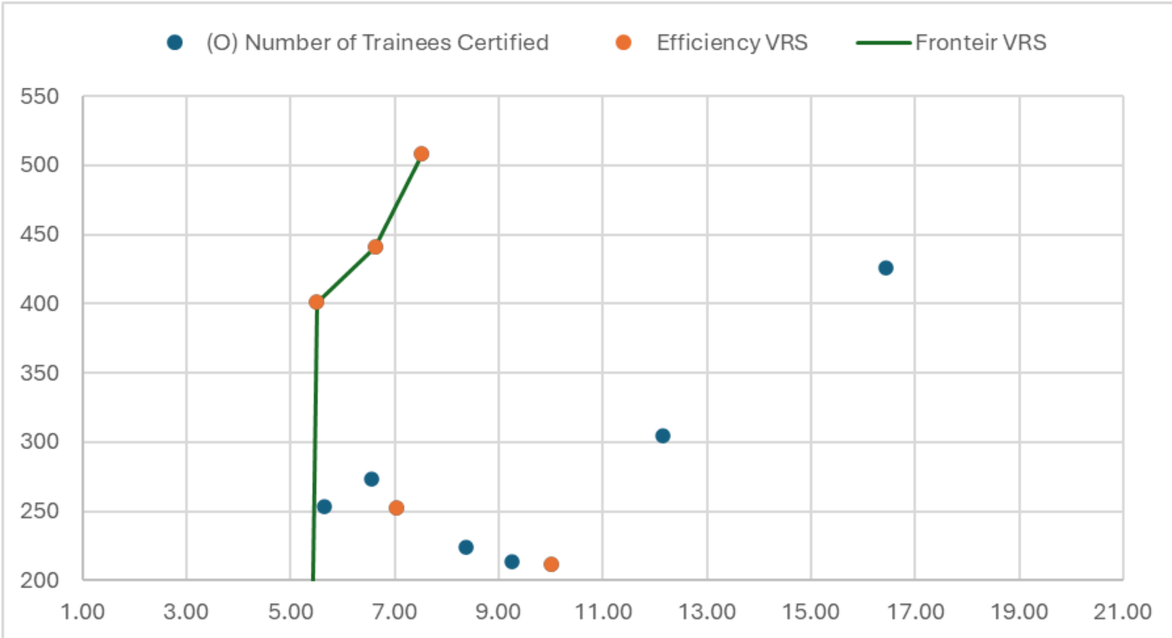

Figure 4.6: Cluster 2 Efficiency Frontier — Input 2 (Trainer Experience) vs. Output (Certified Trainees)

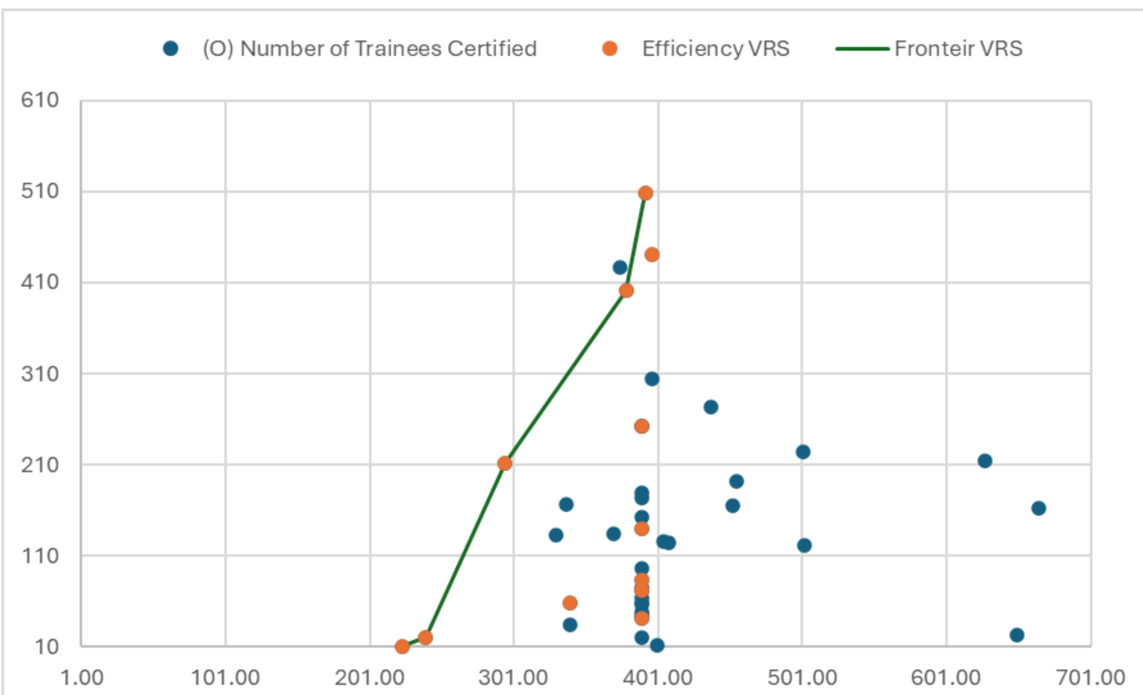

Figure 4.7: Cluster 2 Efficiency Frontier — Input 3 (Course Duration) vs. Output (Certified Trainees)

Cluster 3

The efficiency frontier plots for Cluster 3 illustrate how the 61 DMUs in this segment convert resources into certified trainees. As with the other clusters, training providers that appear on the efficiency frontier are deemed fully efficient (PTE=1.0) and set the benchmark for technical efficiency in their operational environment. Cluster 3 features 13 efficient DMUs, of which 11 are Industry-integrated and 2 is Center-Based.

Table 4.9: List of Efficient DMUs in Cluster 3

DMU Number	DMU Type	PTE	Scale Efficiency
Cluster 3_1	Industry-Integrated TP	1.0000	0.9000
Cluster 3_2	Industry-Integrated TP	1.0000	0.7391
Cluster 3_6	Industry-Integrated TP	1.0000	0.5235
Cluster 3_10	Industry-Integrated TP	1.0000	1.0000
Cluster 3_13	Industry-Integrated TP	1.0000	1.0000
Cluster 3_14	Industry-Integrated TP	1.0000	0.9662
Cluster 3_16	Industry-Integrated TP	1.0000	0.6400
Cluster 3_19	Industry-Integrated TP	1.0000	0.8889
Cluster 3_25	Industry-Integrated TP	1.0000	0.8333
Cluster 3_28	Industry-Integrated TP	1.0000	0.9667
Cluster 3_29	Industry-Integrated TP	1.0000	1.0000
Cluster 3_44	Center Based TP	1.0000	0.9841
Cluster 3_58	Center Based TP	1.0000	1.0000

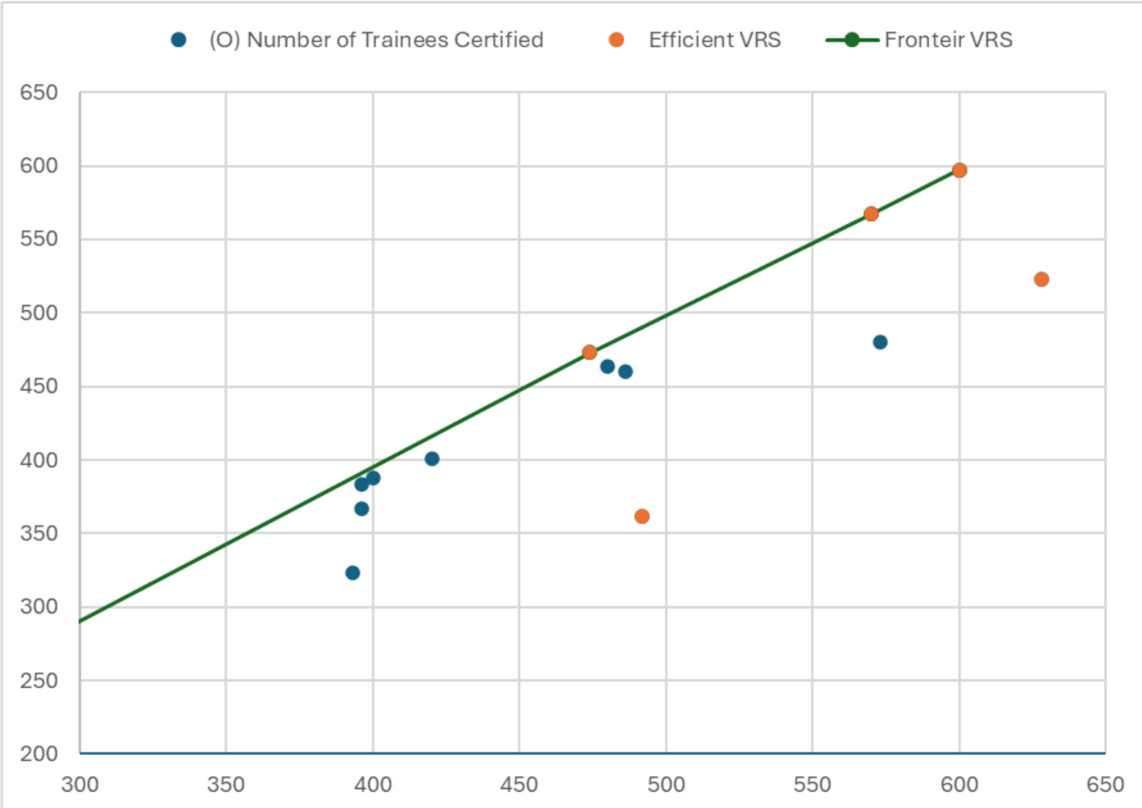

Figure 4.8: Cluster 3 Efficiency Frontier — Input 1 (Enrolled Trainees) vs. Output (Certified Trainees)

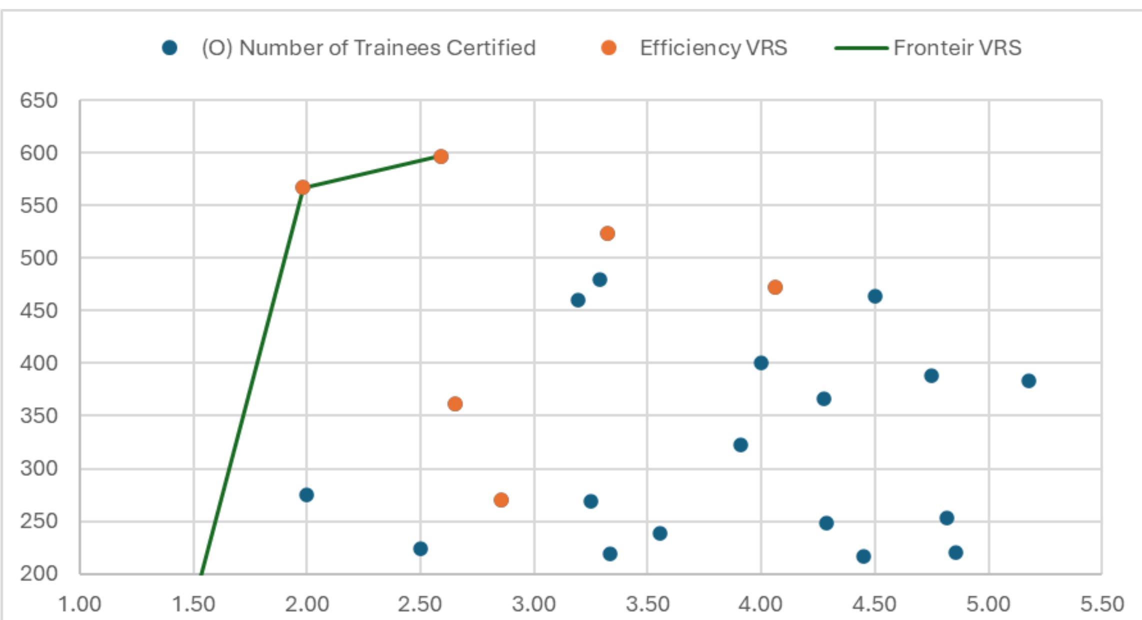

Figure 4.9: Cluster 3 Efficiency Frontier — Input 2 (Trainer Experience) vs. Output (Certified Trainees)

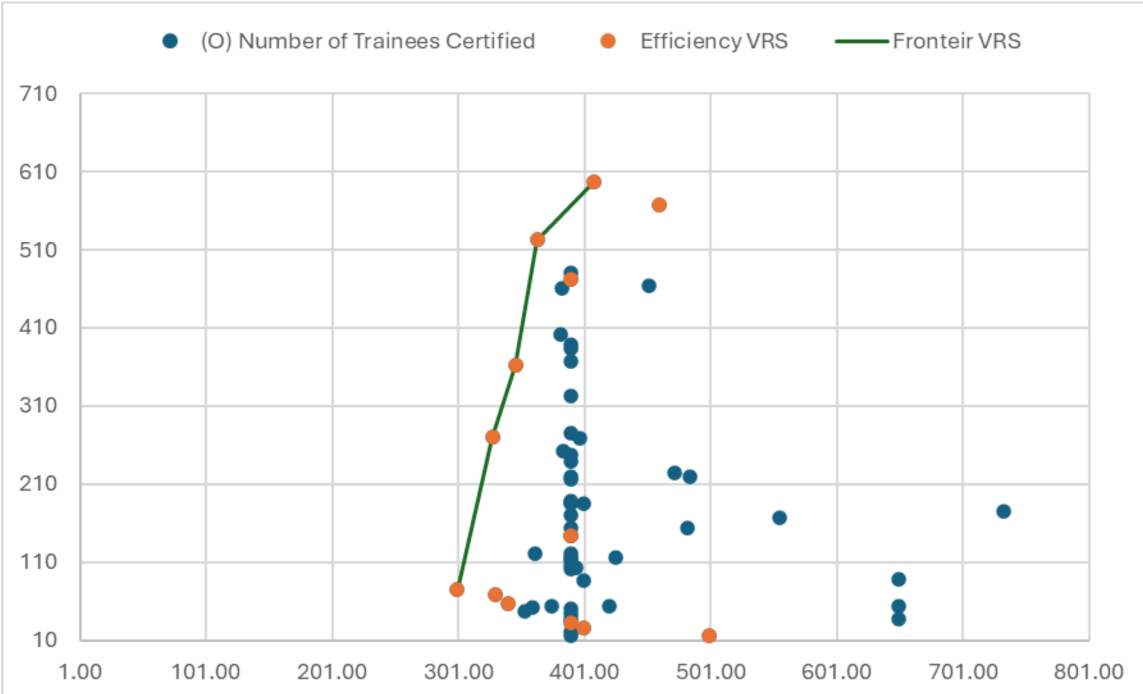

Figure 4.10: Cluster 3 Efficiency Frontier — Input 3 (Course Duration) vs. Output (Certified Trainees)

Global DEA

The global efficiency frontier reflects best-practice performance across all 134 training providers, offering a universal benchmark that extends beyond the boundaries of individual clusters. Providers positioned on this frontier have attained a Pure Technical Efficiency (PTE) score of 1.0, placing them among the most efficient in the entire system. In total, 24 DMUs achieved this benchmark, representing roughly 18% of the dataset. These top-tier performers serve as a reference point for technical excellence across the skill training ecosystem.

The remaining DMUs, situated below the frontier, highlight the broader potential for efficiency improvement across the system. By identifying the gap between current performance and the best-practice frontier, the global DEA model offers a comprehensive framework for benchmarking. This system-wide lens is especially valuable for policymakers and administrators, providing actionable insights that can inform targeted interventions, resource allocation, and strategies to elevate overall provider performance.

Table 4.10: List of Efficient TPs (Global DEA)

DMU_Number	Cluster DMU Number	DMU Type	PTE	Scale Efficiency
2	Cluster 3_1	Industry-Integrated	1	0.9000
8	Cluster 2_3	Industry-Integrated	1	1.0000
13	Cluster 3_6	Industry-Integrated	1	0.5235
19	Cluster 2_9	Industry-Integrated	1	0.8400
23	Cluster 1_3	Industry-Integrated	1	1.0000
25	Cluster 3_10	Industry-Integrated	1	1.0000
30	Cluster 2_15	Industry-Integrated	1	0.9833
31	Cluster 3_13	Industry-Integrated	1	1.0000
35	Cluster 3_14	Industry-Integrated	1	0.9662
40	Cluster 3_16	Industry-Integrated	1	0.6400
41	Cluster 2_18	Industry-Integrated	1	1.0000
47	Cluster 3_19	Industry-Integrated	1	0.8889
50	Cluster 2_22	Industry-Integrated	1	0.4400
57	Cluster 1_11	Industry-Integrated	1	1.0000
59	Cluster 1_13	Industry-Integrated	1	0.9908
63	Cluster 3_28	Industry-Integrated	1	0.9667
65	Cluster 3_29	Industry-Integrated	1	1.0000
70	Cluster 1_16	Industry-Integrated	1	0.9752
77	Cluster 2_25	Center-based	1	1.0000
95	Cluster 2_34	Center-based	1	1.0000
96	Cluster 1_20	Center-based	1	1.0000
119	Cluster 2_39	Center-based	1	0.9545
128	Cluster 1_31	Center-based	1	1.0000
130	Cluster 3_58	Center-based	1	1.0000

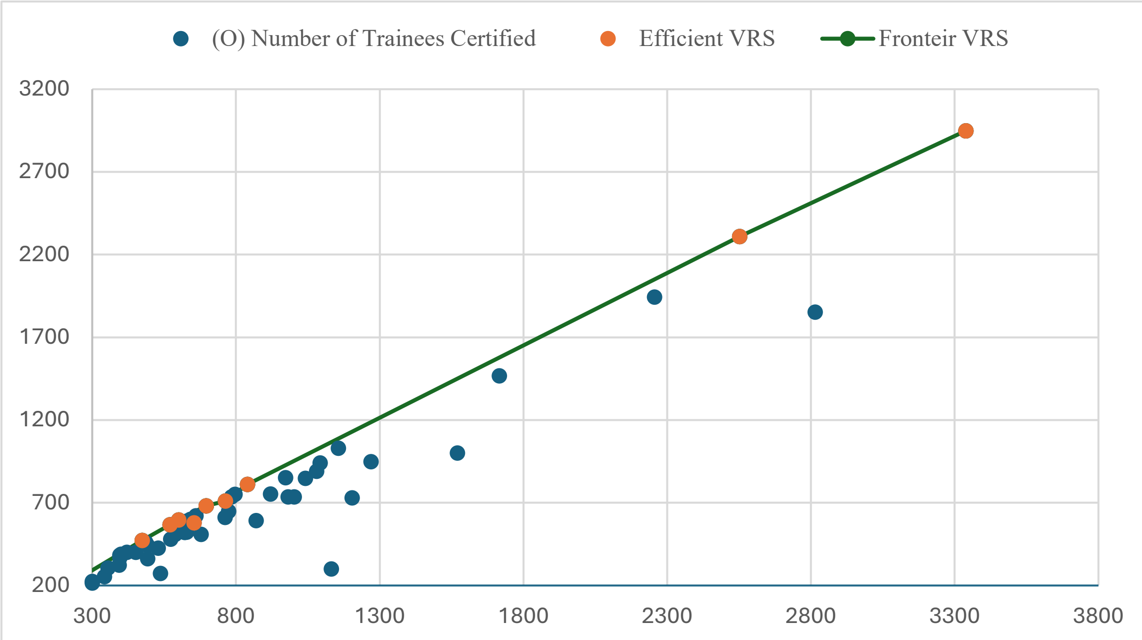

Figure 4.11: All DMUs Efficiency Frontier - Input 1 (Enrolled Trainees) vs. Output (Certified Trainees)

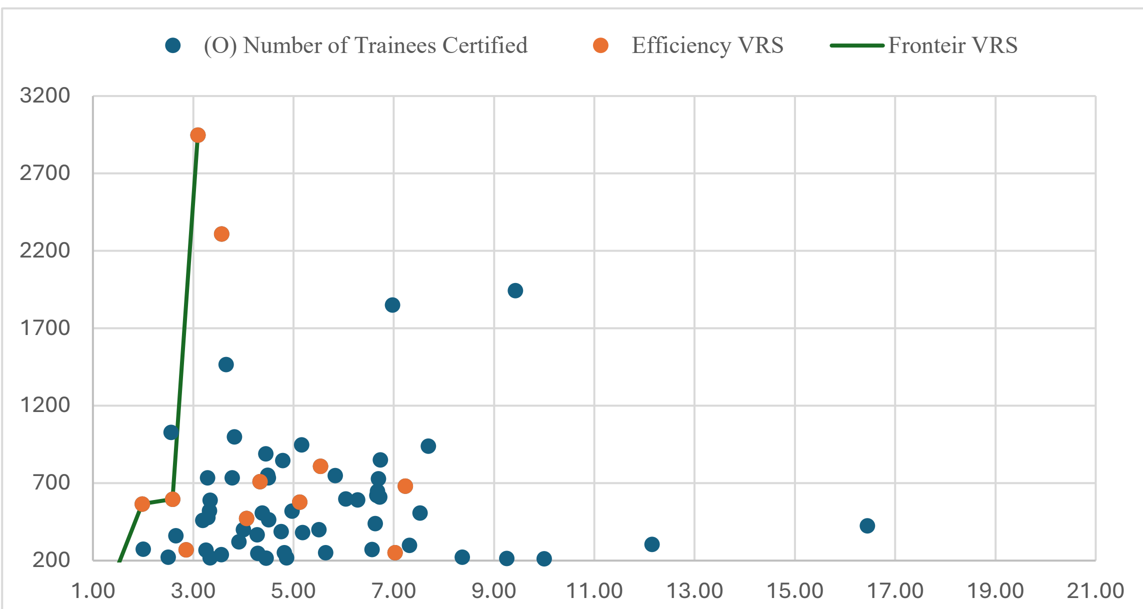

Figure 4.12: All DMUs Efficiency Frontier - Input 2 (Trainer Experience) vs. Output (Certified Trainees)

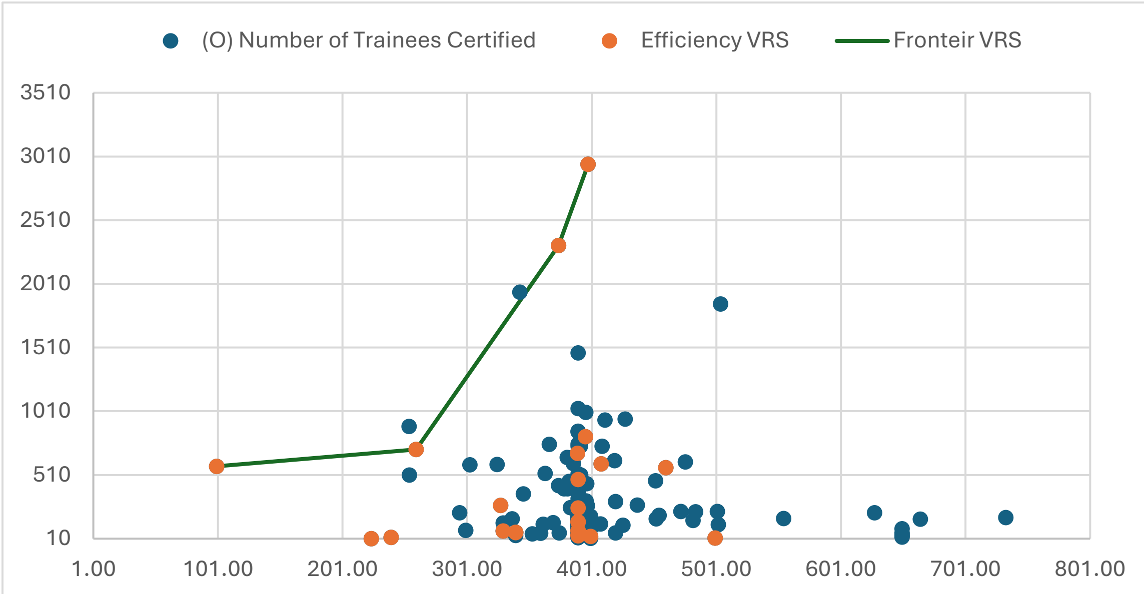

Figure 4.13: All DMUs Efficiency Frontier - Input 3 (Course Duration) vs. Output (Certified Trainees)

4.2.3 Scale Efficiency Analysis

Scale efficiency reflects whether a training provider (DMU) is operating at its most productive scale size. It is calculated as the ratio of Overall Technical Efficiency (CRS) to Pure Technical Efficiency (VRS). A score of 1 indicates optimal scale, while scores below 1 suggest inefficiencies due to either increasing or decreasing returns to scale. Please refer Table 4.3 with the SE Scores cluster-wise.

The results indicate that Cluster 1 providers are closest to operating at optimal scale, with the highest average and lowest variability in scale efficiency. Cluster 2 shows the widest range and highest standard deviation, suggesting greater scale-related inefficiencies. Cluster 3 lies in between, with moderate average efficiency and variability.

4.2.4 Peer Benchmarking

In Data Envelopment Analysis, peer benchmarking is a critical tool for identifying reference units for inefficient Decision-Making Units (DMUs). This process is guided by the λ (lambda) weights, which are derived during the DEA optimization. These weights indicate how much each efficient DMU contributes to forming the efficiency frontier for a given inefficient DMU.

Benchmarking Logic

- Each inefficient DMU is benchmarked against a convex combination of efficient DMUs.
- The λ weights represent the contribution of each efficient peer in constructing the target output for the inefficient DMU.
- DMUs with higher λ values are considered closer peers and more influential in the benchmarking process.
- This allows inefficient providers to identify specific efficient peers whose operational models they can emulate.

Cluster-wise Benchmarking Tables

Cluster 1

Table 4.11: Peer Benchmarking for Cluster 1 DMUs

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
Cluster 1_1	Cluster 1_13 (0.081)	Cluster 1_16 (0.079)	Cluster 1_20 (0.839)
Cluster 1_2	Cluster 1_3 (0.443)	Cluster 1_13 (0.516)	Cluster 1_20 (0.041)
Cluster 1_4	Cluster 1_3 (0.078)	Cluster 1_20 (0.442)	Cluster 1_24 (0.480)
Cluster 1_6	Cluster 1_3 (0.501)	Cluster 1_11 (0.411)	Cluster 1_13 (0.088)
Cluster 1_7	Cluster 1_13 (0.644)	Cluster 1_16 (0.169)	Cluster 1_20 (0.187)
Cluster 1_8	Cluster 1_5 (0.409)	Cluster 1_11 (0.096)	Cluster 1_13 (0.273)
Cluster 1_9	Cluster 1_3 (0.599)	Cluster 1_11 (0.196)	Cluster 1_13 (0.205)
Cluster 1_10	Cluster 1_5 (0.723)	Cluster 1_20 (0.162)	Cluster 1_22 (0.115)
Cluster 1_12	Cluster 1_3 (0.853)	Cluster 1_20 (0.147)	-
Cluster 1_14	Cluster 1_5 (0.545)	Cluster 1_11 (0.455)	-
Cluster 1_15	Cluster 1_3 (0.830)	Cluster 1_20 (0.170)	-
Cluster 1_17	Cluster 1_5 (0.818)	Cluster 1_11 (0.182)	-

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
Cluster 1_19	Cluster 1_3 (0.458)	Cluster 1_11 (0.542)	-
Cluster 1_21	Cluster 1_20 (0.667)	Cluster 1_31 (0.333)	-
Cluster 1_23	Cluster 1_3 (0.783)	Cluster 1_13 (0.004)	Cluster 1_20 (0.213)
Cluster 1_25	Cluster 1_3 (0.416)	Cluster 1_5 (0.027)	Cluster 1_20 (0.066)
Cluster 1_26	Cluster 1_3 (0.594)	Cluster 1_5 (0.024)	Cluster 1_20 (0.129)
Cluster 1_27	Cluster 1_3 (0.889)	Cluster 1_13 (0.032)	Cluster 1_20 (0.079)
Cluster 1_28	Cluster 1_5 (0.028)	Cluster 1_20 (0.530)	Cluster 1_24 (0.442)
Cluster 1_29	Cluster 1_3 (0.749)	Cluster 1_20 (0.251)	-
Cluster 1_30	Cluster 1_3 (0.426)	Cluster 1_5 (0.021)	Cluster 1_20 (0.100)

Table 4. 12: Most Frequently Referenced Efficient Peers in Cluster 1

Cluster 1	
DMU No.	Reference Frequency
Cluster 1_20	15
Cluster 1_3	13
Cluster 1_5	8
Cluster 1_13	8
Cluster 1_11	6

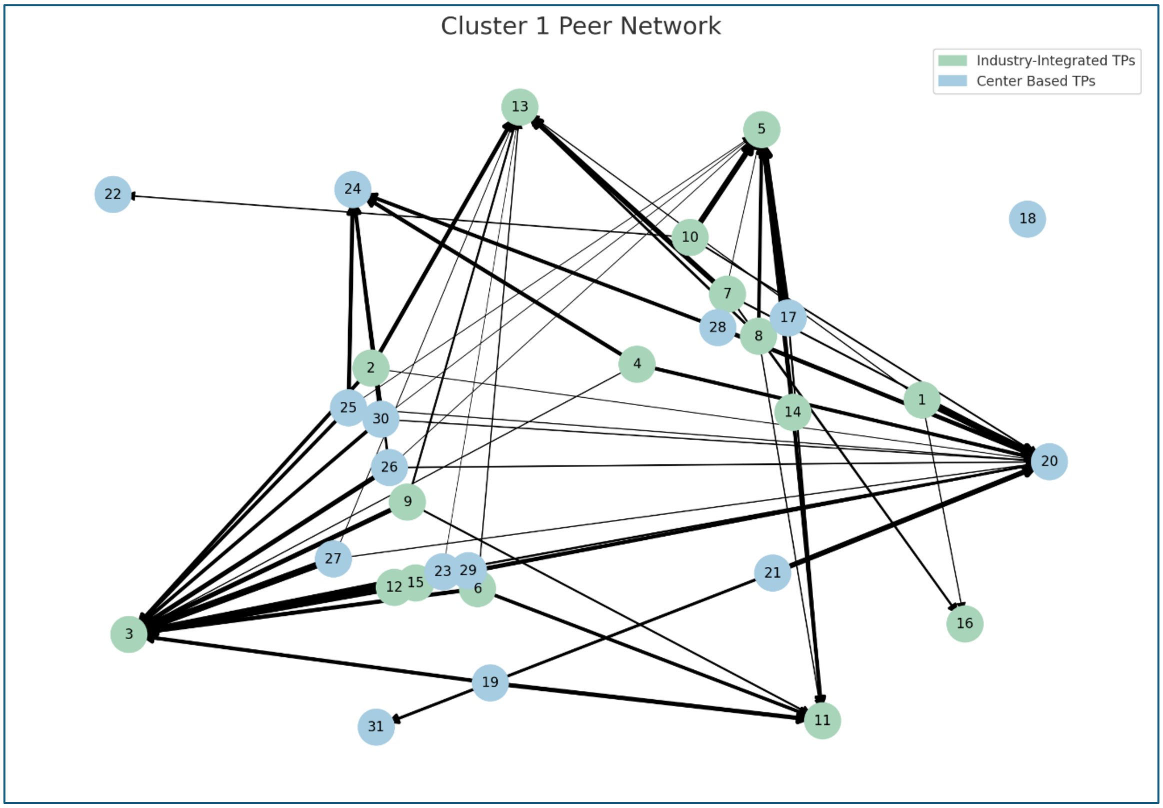

Figure 4.14: Peer Network Diagram for Cluster 1

Cluster 2

Table 4.13: Peer Benchmarking for Cluster 2 DMUs

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
Cluster 2_1	Cluster 2_4 (0.099)	Cluster 2_9 (0.168)	Cluster 2_22 (0.153)
Cluster 2_2	Cluster 2_9 (0.632)	Cluster 2_39 (0.368)	-
Cluster 2_6	Cluster 2_18 (0.421)	Cluster 2_25 (0.238)	Cluster 2_34 (0.341)
Cluster 2_8	Cluster 2_28 (0.525)	Cluster 2_33 (0.475)	-
Cluster 2_10	Cluster 2_22 (0.551)	Cluster 2_34 (0.401)	Cluster 2_39 (0.048)
Cluster 2_11	Cluster 2_3 (0.049)	Cluster 2_15 (0.400)	Cluster 2_18 (0.091)
Cluster 2_12	Cluster 2_18 (0.329)	Cluster 2_25 (0.557)	Cluster 2_34 (0.114)
Cluster 2_13	Cluster 2_3 (0.694)	Cluster 2_18 (0.172)	Cluster 2_25 (0.133)
Cluster 2_14	Cluster 2_3 (0.101)	Cluster 2_18 (0.299)	Cluster 2_25 (0.600)
Cluster 2_16	Cluster 2_25 (0.307)	Cluster 2_33 (0.179)	Cluster 2_34 (0.514)
Cluster 2_17	Cluster 2_3 (0.129)	Cluster 2_18 (0.538)	Cluster 2_25 (0.333)
Cluster 2_19	Cluster 2_9 (0.737)	Cluster 2_39 (0.263)	-
Cluster 2_20	Cluster 2_5 (0.200)	Cluster 2_25 (0.800)	-
Cluster 2_21	Cluster 2_3 (0.290)	Cluster 2_18 (0.632)	Cluster 2_25 (0.078)

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
Cluster 2_23	Cluster 2_25 (0.417)	Cluster 2_33 (0.075)	Cluster 2_34 (0.508)
Cluster 2_24	Cluster 2_9 (0.075)	Cluster 2_15 (0.776)	Cluster 2_39 (0.149)
Cluster 2_26	Cluster 2_18 (0.235)	Cluster 2_34 (0.765)	-
Cluster 2_27	Cluster 2_22 (0.106)	Cluster 2_28 (0.894)	-
Cluster 2_29	Cluster 2_25 (0.055)	Cluster 2_33 (0.106)	Cluster 2_34 (0.840)
Cluster 2_30	Cluster 2_3 (0.417)	Cluster 2_25 (0.583)	-
Cluster 2_31	Cluster 2_5 (0.200)	Cluster 2_25 (0.800)	-
Cluster 2_32	Cluster 2_18 (0.260)	Cluster 2_25 (0.604)	Cluster 2_34 (0.136)
Cluster 2_35	Cluster 2_9 (0.162)	Cluster 2_22 (0.575)	Cluster 2_39 (0.263)
Cluster 2_36	Cluster 2_25 (0.106)	Cluster 2_33 (0.611)	Cluster 2_34 (0.282)
Cluster 2_37	Cluster 2_22 (0.295)	Cluster 2_25 (0.167)	Cluster 2_33 (0.342)
Cluster 2_38	Cluster 2_7 (0.296)	Cluster 2_22 (0.449)	Cluster 2_34 (0.255)
Cluster 2_40	Cluster 2_3 (0.533)	Cluster 2_25 (0.467)	-
Cluster 2_41	Cluster 2_5 (0.425)	Cluster 2_25 (0.575)	-
Cluster 2_42	Cluster 2_3 (0.429)	Cluster 2_39 (0.571)	-

Table 4.14: Most Frequently Referenced Efficient Peers in Cluster 2

Cluster 2	
DMU No	**Reference Frequency**
Cluster 2_25	19
Cluster 2_34	11
Cluster 2_18	9
Cluster 2_3	8
Cluster 2_22	6

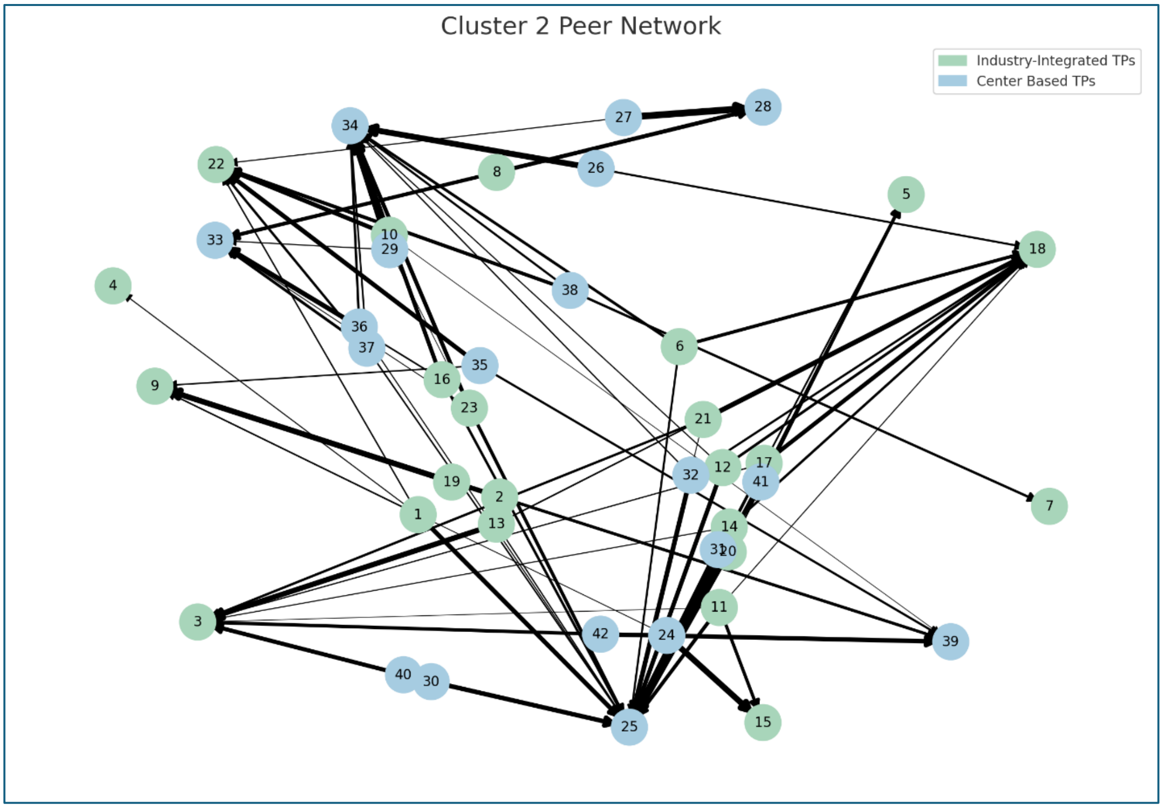

Figure 4.15: Peer Network Diagram for Cluster 2

Cluster 3

Table 4.15: Peer Benchmarking for Cluster 3 DMUs

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
Cluster 3_3	Cluster 3_28 (0.643)	Cluster 3_29 (0.357)	
Cluster 3_4	Cluster 3_13 (0.002)	Cluster 3_19 (0.788)	Cluster 3_29 (0.210)
Cluster 3_5	Cluster 3_19 (0.021)	Cluster 3_29 (0.644)	Cluster 3_58 (0.334)
Cluster 3_7	Cluster 3_28 (1.000)		
Cluster 3_8	Cluster 3_10 (0.048)	Cluster 3_58 (0.952)	
Cluster 3_9	Cluster 3_10 (0.001)	Cluster 3_14 (0.076)	Cluster 3_19 (0.717)
Cluster 3_11	Cluster 3_28 (0.643)	Cluster 3_29 (0.357)	
Cluster 3_12	Cluster 3_1 (0.273)	Cluster 3_19 (0.336)	Cluster 3_28 (0.055)
Cluster 3_15	Cluster 3_1 (0.800)	Cluster 3_28 (0.200)	
Cluster 3_17	Cluster 3_13 (0.002)	Cluster 3_19 (0.788)	Cluster 3_29 (0.210)
Cluster 3_18	Cluster 3_13 (0.142)	Cluster 3_19 (0.346)	Cluster 3_29 (0.401)
Cluster 3_20	Cluster 3_6 (0.026)	Cluster 3_10 (0.402)	Cluster 3_14 (0.094)
Cluster 3_21	Cluster 3_13 (0.106)	Cluster 3_19 (0.264)	Cluster 3_29 (0.293)
Cluster 3_22	Cluster 3_13 (0.141)	Cluster 3_19 (0.222)	Cluster 3_29 (0.638)
Cluster 3_23	Cluster 3_14 (0.047)	Cluster 3_28 (0.109)	Cluster 3_58 (0.845)
Cluster 3_24	Cluster 3_29 (0.236)	Cluster 3_58 (0.764)	

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
Cluster 3_26	Cluster 3_29 (0.921)	Cluster 3_58 (0.079)	
Cluster 3_27	Cluster 3_10 (0.018)	Cluster 3_19 (0.366)	Cluster 3_28 (0.607)
Cluster 3_30	Cluster 3_28 (0.560)	Cluster 3_29 (0.279)	Cluster 3_58 (0.161)
Cluster 3_31	Cluster 3_13 (0.068)	Cluster 3_19 (0.103)	Cluster 3_29 (0.828)
Cluster 3_32	Cluster 3_1 (0.352)	Cluster 3_19 (0.296)	Cluster 3_28 (0.070)
Cluster 3_33	Cluster 3_19 (0.345)	Cluster 3_29 (0.581)	Cluster 3_58 (0.074)
Cluster 3_34	Cluster 3_29 (0.897)	Cluster 3_58 (0.103)	
Cluster 3_35	Cluster 3_19 (0.498)	Cluster 3_29 (0.024)	Cluster 3_58 (0.478)
Cluster 3_36	Cluster 3_19 (0.079)	Cluster 3_29 (0.141)	Cluster 3_58 (0.780)
Cluster 3_37	Cluster 3_29 (0.942)	Cluster 3_58 (0.058)	
Cluster 3_38	Cluster 3_28 (1.000)		
Cluster 3_39	Cluster 3_19 (0.313)	Cluster 3_29 (0.285)	Cluster 3_58 (0.402)
Cluster 3_40	Cluster 3_10 (0.207)	Cluster 3_19 (0.590)	Cluster 3_28 (0.076)
Cluster 3_41	Cluster 3_10 (0.502)	Cluster 3_14 (0.264)	Cluster 3_58 (0.234)
Cluster 3_42	Cluster 3_29 (0.673)	Cluster 3_58 (0.327)	
Cluster 3_43	Cluster 3_1 (0.273)	Cluster 3_19 (0.336)	Cluster 3_28 (0.055)
Cluster 3_45	Cluster 3_28 (0.120)	Cluster 3_29 (0.443)	Cluster 3_58 (0.437)
Cluster 3_46	Cluster 3_29 (0.709)	Cluster 3_58 (0.291)	
Cluster 3_47	Cluster 3_13 (0.327)	Cluster 3_19 (0.372)	Cluster 3_29 (0.301)
Cluster 3_48	Cluster 3_19 (0.237)	Cluster 3_29 (0.321)	Cluster 3_58 (0.441)
Cluster 3_49	Cluster 3_10 (0.207)	Cluster 3_19 (0.590)	Cluster 3_28 (0.076)
Cluster 3_50	Cluster 3_14 (0.044)	Cluster 3_19 (0.418)	Cluster 3_25 (0.176)
Cluster 3_51	Cluster 3_28 (0.131)	Cluster 3_29 (0.869)	
Cluster 3_52	Cluster 3_13 (0.057)	Cluster 3_19 (0.458)	Cluster 3_29 (0.391)
Cluster 3_53	Cluster 3_29 (0.224)	Cluster 3_58 (0.776)	
Cluster 3_54	Cluster 3_29 (0.709)	Cluster 3_58 (0.291)	
Cluster 3_55	Cluster 3_10 (0.671)	Cluster 3_14 (0.104)	Cluster 3_44 (0.225)
Cluster 3_56	Cluster 3_1 (0.073)	Cluster 3_19 (0.226)	Cluster 3_28 (0.015)
Cluster 3_57	Cluster 3_19 (0.331)	Cluster 3_29 (0.397)	Cluster 3_58 (0.272)
Cluster 3_59	Cluster 3_28 (0.429)	Cluster 3_29 (0.571)	
Cluster 3_60	Cluster 3_19 (0.122)	Cluster 3_29 (0.620)	Cluster 3_58 (0.258)
Cluster 3_61	Cluster 3_29 (0.236)	Cluster 3_58 (0.764)	

Table 4.16: Most Frequently Referenced Efficient Peers in Cluster 3

Cluster 3	
DMU No	**Reference Frequency**
Cluster 3_29	35
Cluster 3_58	28
Cluster 3_19	26
Cluster 3_28	19

Cluster 3	
DMU No	**Reference Frequency**
Cluster 3_13	8

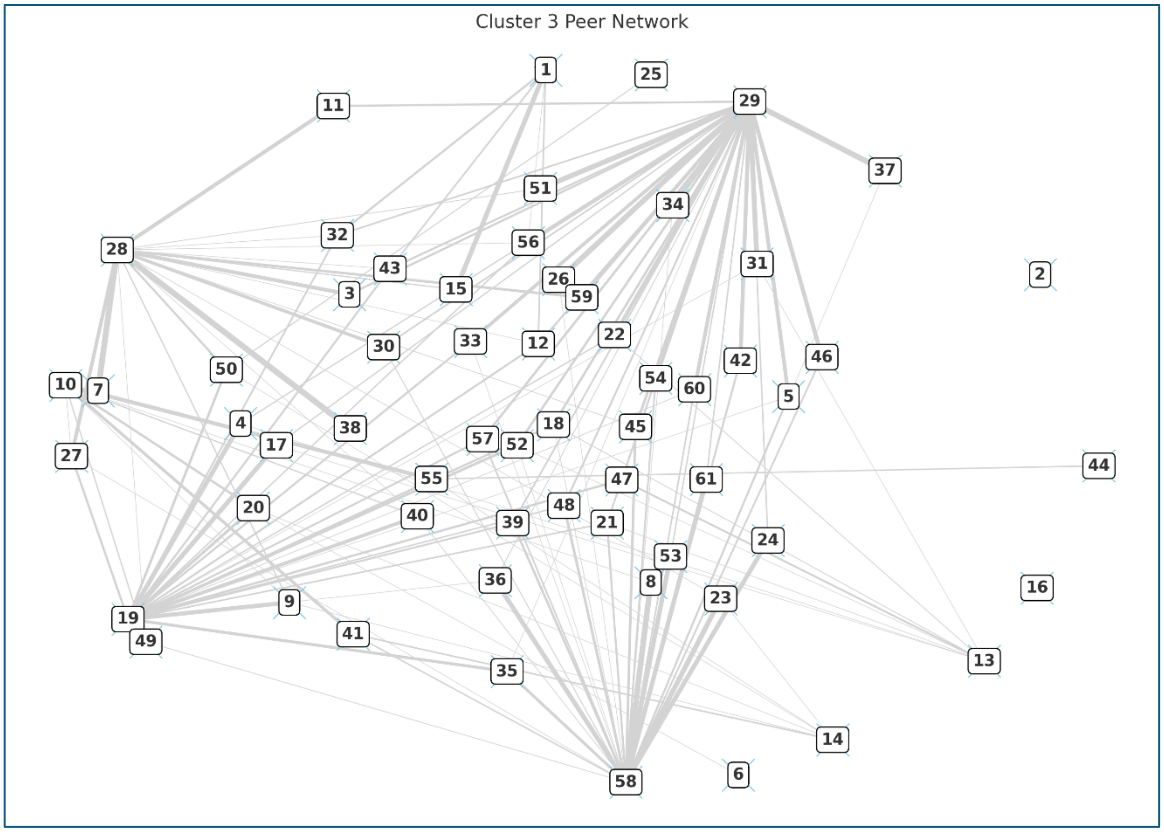

Figure 4.16: Peer Network Diagram for Cluster 3

Global Benchmarking Table

Table 4.17: Global Benchmarking Table of Inefficient DMUs and Peer References

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
1	19 (0.337)	30 (0.189)	77 (0.299)
3	25 (0.444)	47 (0.340)	70 (0.178)
4	2 (0.286)	41 (0.298)	65 (0.417)
5	31 (0.002)	47 (0.788)	65 (0.210)
6	59 (0.081)	70 (0.079)	96 (0.839)
7	2 (0.892)	19 (0.035)	30 (0.073)
9	19 (0.628)	25 (0.347)	70 (0.025)
10	47 (0.021)	65 (0.644)	130 (0.334)
11	25 (0.143)	130 (0.857)	
12	8 (0.263)	65 (0.617)	77 (0.120)
14	2 (0.393)	41 (0.545)	65 (0.062)
15	25 (0.048)	130 (0.952)	
16	23 (0.443)	59 (0.516)	96 (0.041)
17	41 (0.481)	47 (0.041)	65 (0.479)
18	25 (0.500)	130 (0.500)	
20	41 (0.781)	47 (0.146)	65 (0.073)
21	8 (0.096)	30 (0.400)	65 (0.074)
22	25 (0.001)	35 (0.076)	47 (0.717)
24	8 (0.185)	65 (0.359)	77 (0.456)
26	8 (0.783)	65 (0.140)	77 (0.077)
27	8 (0.254)	65 (0.243)	77 (0.503)
28	2 (0.357)	41 (0.185)	65 (0.458)
29	41 (0.149)	47 (0.568)	65 (0.284)
32	65 (0.353)	77 (0.574)	130 (0.073)
33	23 (0.264)	25 (0.272)	96 (0.464)
34	25 (0.531)	47 (0.102)	70 (0.331)
36	23 (0.501)	57 (0.411)	59 (0.088)
37	2 (0.741)	30 (0.148)	119 (0.111)
38	8 (0.405)	65 (0.437)	77 (0.159)
39	59 (0.644)	70 (0.169)	96 (0.187)
42	2 (1.000)		
43	31 (0.002)	47 (0.788)	65 (0.210)
44	31 (0.142)	47 (0.346)	65 (0.401)
45	25 (0.261)	57 (0.080)	59 (0.319)
46	77 (0.784)	130 (0.216)	
48	8 (0.413)	41 (0.393)	65 (0.194)
49	25 (0.400)	35 (0.097)	47 (0.499)
51	23 (0.599)	57 (0.196)	59 (0.205)

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
52	31 (0.106)	47 (0.264)	65 (0.293)
53	23 (0.174)	25 (0.641)	96 (0.185)
54	31 (0.141)	47 (0.222)	65 (0.638)
55	25 (0.056)	50 (0.018)	63 (0.128)
56	77 (0.351)	130 (0.649)	
58	23 (0.853)	96 (0.147)	
60	35 (0.214)	47 (0.150)	50 (0.387)
61	65 (0.913)	77 (0.013)	130 (0.075)
62	25 (0.018)	47 (0.366)	63 (0.607)
64	8 (0.006)	65 (0.379)	77 (0.615)
66	30 (0.394)	63 (0.166)	65 (0.279)
67	31 (0.068)	47 (0.103)	65 (0.828)
68	23 (0.250)	25 (0.750)	
69	23 (0.830)	96 (0.170)	
71	41 (0.191)	47 (0.595)	65 (0.214)
72	2 (0.098)	19 (0.059)	30 (0.843)
73	47 (0.345)	65 (0.581)	130 (0.074)
74	65 (0.709)	77 (0.279)	130 (0.012)
75	47 (0.498)	65 (0.024)	130 (0.478)
76	47 (0.079)	65 (0.141)	130 (0.780)
78	8 (0.198)	41 (0.079)	65 (0.722)
79	65 (0.860)	77 (0.122)	130 (0.018)
80	41 (0.660)	47 (0.338)	65 (0.002)
81	47 (0.313)	65 (0.285)	130 (0.402)
82	19 (0.127)	25 (0.832)	70 (0.041)
83	19 (0.025)	25 (0.936)	70 (0.039)
84	41 (0.049)	65 (0.594)	77 (0.357)
85	8 (0.417)	77 (0.583)	
86	25 (0.207)	47 (0.590)	63 (0.076)
87	25 (0.694)	50 (0.097)	63 (0.077)
88	25 (0.542)	57 (0.411)	70 (0.047)
89	25 (0.750)	57 (0.202)	70 (0.048)
90	77 (0.784)	130 (0.216)	
91	23 (0.675)	25 (0.325)	
92	8 (0.152)	65 (0.321)	77 (0.527)
93	65 (0.547)	77 (0.188)	130 (0.266)
94	19 (0.094)	25 (0.151)	130 (0.755)
97	96 (0.667)	128 (0.333)	
98	41 (0.149)	47 (0.568)	65 (0.284)
99	25 (0.737)	57 (0.070)	59 (0.100)
100	2 (1.000)		
101	25 (0.306)	31 (0.003)	47 (0.315)

DMU No.	Peer 1 (λ)	Peer 2 (λ)	Peer 3 (λ)
102	23 (0.783)	59 (0.004)	96 (0.213)
103	65 (0.047)	77 (0.525)	130 (0.428)
104	30 (0.120)	65 (0.381)	77 (0.093)
105	19 (0.245)	30 (0.015)	63 (0.306)
106	41 (0.714)	47 (0.135)	65 (0.151)
107	23 (0.344)	25 (0.537)	59 (0.074)
108	65 (0.690)	77 (0.029)	130 (0.281)
109	23 (0.580)	25 (0.276)	59 (0.056)
110	31 (0.327)	47 (0.372)	65 (0.301)
111	23 (0.677)	25 (0.147)	59 (0.036)
112	47 (0.237)	65 (0.321)	130 (0.441)
113	25 (0.207)	47 (0.590)	63 (0.076)
114	35 (0.082)	47 (0.445)	50 (0.068)
115	41 (0.078)	47 (0.050)	65 (0.872)
116	23 (0.889)	59 (0.032)	96 (0.079)
117	31 (0.057)	47 (0.458)	65 (0.391)
118	65 (0.076)	77 (0.221)	130 (0.703)
120	8 (0.533)	77 (0.467)	
121	23 (0.178)	25 (0.272)	96 (0.550)
122	65 (0.635)	77 (0.110)	130 (0.255)
123	19 (0.050)	25 (0.917)	70 (0.033)
124	23 (0.749)	96 (0.251)	
125	41 (0.040)	47 (0.288)	65 (0.672)
126	23 (0.578)	25 (0.253)	59 (0.049)
127	47 (0.331)	65 (0.397)	130 (0.272)
129	77 (0.541)	130 (0.459)	
131	41 (0.287)	47 (0.142)	65 (0.571)
132	47 (0.122)	65 (0.620)	130 (0.258)
133	8 (0.429)	119 (0.571)	
134	65 (0.209)	77 (0.040)	130 (0.751)

Table 4.18: Most Frequently Referenced Efficient Peers for Global DEA

All	
DMU No	**Reference Frequency**
65	53
130	39
47	36
25	32
77	28

4.2.5 Tobit Regression Analysis

Building on the quantitative efficiency assessment presented earlier, it is important to consider the influence of social demographics on certification outcomes. This section explores how the gender and caste composition of training cohorts may shape efficiency levels, adding a layer of socio-contextual insight to the operational analysis. By examining these demographic factors, the analysis moves beyond input-output metrics to offer a more nuanced understanding of what drives or hinders performance across training providers.

Tobit regression was employed to examine the relationship between environmental variables and Pure Technical Efficiency scores. Given that efficiency scores are bounded between 0 and 1, the censored regression model is appropriate for this analysis.

Environmental Variables:

- Percentage of female trainees (gender inclusivity indicator)
- Percentage of SC/ST/OBC trainees (social inclusion measure)

Interpretation & Implications

The regression results summarized in Table 4.18 indicate a statistically significant positive relationship between the proportion of female trainees enrolled and certification efficiency. Specifically, training providers with higher female participation tend to perform more efficiently, as reflected by a coefficient of 0.00169 ($p = 0.018$). This suggests that gender inclusion may be an influential factor in driving better outcomes—possibly linked to higher levels of engagement, more responsive program design, or socio-cultural dynamics that support the success of female trainees.

In contrast, the share of trainees from SC/ST/OBC backgrounds does not show a statistically significant association with efficiency (coefficient = -0.0005; p = 0.404). While this finding does not imply that caste is unimportant, it does suggest that its influence on efficiency may be more complex or mediated by other contextual factors. From a policy standpoint, caste equity remains vital for ensuring access and fairness, even if its direct effect on operational efficiency appears muted in this model.

These findings highlight that efficiency in skill training is shaped not only by operational inputs but also by the social composition of trainee cohorts. Gender diversity, in particular, emerges as a potential structural advantage, offering an avenue for both performance gains and equity enhancement. This underscores the need for further exploration into how gender-inclusive practices can be systematically integrated into training programs to optimize outcomes.

That said, several limitations must be acknowledged. DEA scores and the regression analysis are sensitive to the selection of inputs, outputs, and contextual variables. In this case, gender and caste were the only environmental variables included, while other potentially significant factors—such as educational background, income level, or prior work experience—were not captured. Moreover, while bootstrap DEA methods were initially considered to improve robustness and provide confidence intervals, they were ultimately not employed due to interpretive complexity within the current analytical framework.

Future research that incorporates a wider array of demographic and institutional variables, along with more advanced DEA techniques, could offer richer insights into the interplay between social context and technical efficiency in the skill development ecosystem.

Table 4.19: Tobit Regression

Variable	Coefficient	p-value	Interpretation
% Female Trainees	0.00169	0.018	Significant positive effect

Variable	Coefficient	p-value	Interpretation
% SC/ST/OBC Trainees	-0.0005	0.404	Not significant

Having considered the statistical associations between social composition and efficiency, the subsequent qualitative analysis explores training providers' operational practices and contextual challenges. This mixed-methods approach enables a richer understanding of the mechanisms underpinning observed efficiency patterns and supports recommendations for policy and practice.

4.3 Qualitative Analysis

This section covers the analysis of the qualitative strand of the research. It is imperative to note here that, for analysis of the TP response and the Certified trainee responses, the TPs are divided in two efficiency groups rather than sticking to the TPs with PTE = 1 and PTE<1.

- TPs which received a PTE >=0.85 are called as High Performing TPs
- TPs which received a PTE < 0.85 are called as Low Performing TPs

Choosing a PTE threshold of 0.85 instead of a perfect 1 makes the grouping more realistic and useful. It acknowledges that in real life, very few institutions are flawless, and small differences or measurement quirks shouldn't exclude those who are still performing well. This way, we include enough high performers to learn from their best practices while also capturing a wide range of experiences.

4.3.1 Training Provider Qualitative Insights

This section presents a synthesis of qualitative findings derived from the in-depth, theme-tagged narrative responses of 42 training providers (TPs) who participated in a qualitative survey administered to the full set of 134 TPs included in the DEA efficiency analysis. Importantly, the qualitative subsample was strategically curated to spotlight providers demonstrating effective or innovative practices. Of the 42 respondents, 28 were categorized as “High Performing” (PTE ≥ 0.85), while 14 were identified as “Low Performing” (PTE < 0.85), based on the output-oriented DEA framework and can be compared against the population representation (Table 4.19). While the response rate may partly reflect the difficulty of securing time from busy institutions, it also aligns with a purposeful sampling strategy designed to capture a wide range of performance experiences. This approach supports both the benchmarking of effective practices and the identification of systemic challenges that may hinder performance.

Unlike traditional surveys that often rely on closed-ended, pre-coded responses, this qualitative assessment draws on open-ended narratives enriched through systematic thematic tagging. This method enables a deeper exploration of provider strategies, obstacles, and contextual factors that help explain observed efficiency trends. The responses touch on a broad array of operational themes—including institutional goals, training logistics, inclusivity efforts, industry collaboration, and placement strategies—offering a textured view of what distinguishes high-performing training providers in real-world settings.

Section 4.3.1 adopts a mixed-methods lens to not only identify which practices correlate with higher efficiency but also understand how providers describe, justify, and tailor these practices within their specific environments. Special focus is given to how Center-Based and Industry-Integrated providers articulate their approaches to candidate mobilization, industry alignment, counselling and support services, trainer recruitment, and equity initiatives. This allows for the identification of both shared challenges and innovative practices unique to each delivery model.

The analysis is further supported by tag frequency counts and statistical associations, offering both qualitative richness and analytical rigor. Taken together, the findings provide actionable insights into the drivers and barriers shaping training provider performance, contributing to a more informed and responsive skill development ecosystem in West Bengal.

Table 4.20: Distribution of TP Type Vs. efficiency scores (for qualitative responses)

Efficiency Group	Center-Based TP	Industry-Integrated TP
High Performing (≥0.85)	16	12
Low Performing (<0.85)	6	8
Total	**22**	**20**

Table 4.21: Efficiency Category (All vs. Qualitative Respnses)

Efficiency Category	High Performing (≥ 0.85)	Low Performing (< 0.85)	Total
All TPs (134)	86 (64.18%)	48 (35.82%)	**134**
Qual. Respondents	28 (66.7%)	14 (33.3%)	**42**

Chi-Square/Fisher's Exact Test: Differences in Key Practice Tags

To explore whether certain operational practices are more commonly associated with higher efficiency, a comparative analysis was conducted using coded thematic tags from the qualitative survey responses. These tags reflect recurring themes—such as strategies, challenges, and interventions—shared by training providers across key functional areas, including candidate mobilization, training delivery, placement, and support services. By applying Chi-Square and Fisher's Exact Tests, the study assessed whether the frequency of specific tags differed significantly between efficient ($PTE \geq 0.85$) and less efficient ($PTE < 0.85$) providers. This approach helps identify which practices are more prevalent among high-performing institutions and may serve as contributing factors to their relative efficiency.

Table 4.22: Chi-Square/Fisher's Exact Test: Differences in Key Practice Tags

Tag	Test Used	P-Value	High Performing - Prevalence	Low Performing - Prevalence
Mobilization Strategy	Chi-Square Test	0.3902	21	14
Counselling Practices	Chi-Square Test	0.2506	52	33
Market-Linked Training	Chi-Square Test	0.4371	36	22
Livelihood Generation	Chi-Square Test	0.0009	10	17
Support for Female Trainees	Chi-Square Test	0.6592	28	16
Support for Marginalized Groups	Chi-Square Test	0.0098	31	29
Infrastructure Challenges	Fisher's Exact Test	0.1686	4	5
Trainer Role	Chi-Square Test	0.0203	13	15
Trainer Recruitment	Chi-Square Test	0.8981	21	11
Placement Challenges	Chi-Square Test	0.6374	43	19
Indicators of Efficiency	Chi-Square Test	0.7482	14	6
Candidate Aspiration	Fisher's Exact Test	0.1686	4	5
Trainee Feedback	Chi-Square Test	0.693	36	20
Training Quality	Chi-Square Test	0.1385	23	18
Placement Focus	Chi-Square Test	0.6011	98	53
Other Significant challenge_Drop-Out	Chi-Square Test	0.4046	16	11
Other Significant challenge_Training Delivery	Chi-Square Test	0.858	11	5
Skill Enhancement	Chi-Square Test	0.6998	38	21

As the statistical analysis of the thematic tags did not reveal significant differences between high- and low-performing training providers, the study pivots toward a deeper examination of the open-ended narrative responses. This shift enables a richer exploration of provider experiences, strategic choices, and sectoral challenges, conveyed in their own words. Such an approach aligns well with established practices in mixed-methods research, where qualitative data are often instrumental in uncovering underlying mechanisms, contextual nuance, and actionable insights that may remain obscured in purely quantitative analysis. The sections that follow draw from these narrative accounts to highlight both common threads and distinctive strategies that shape the functioning and performance of skill training providers across West Bengal. For each TP, responses to the questions were grouped based on efficiency, key themes were identified and their prevalence compared.

Comparison Between High Performing (PTE ≥ 0.85) and Low Performing (PTE < 0.85) Training Providers

This section presents a question-wise thematic comparison of qualitative responses from 42 training providers, categorized by their DEA-based performance. The findings highlight notable contrasts in practices, perceptions, and challenges faced by high-performing and low-performing institutions.

Q1: Primary Objectives of Training Programs

- **High Performing TPs**: Emphasize market-linked skill development, employability, structured job placement, social inclusion (women, minorities), and holistic trainee development.
- **Low Performing TPs**: Offer broad, often generic objectives centred on employment and livelihoods, with limited articulation of market relevance or detailed program goals.

Table 4.23: Comparative Table: Emphasis in Training Objectives

Theme	High Performing TPs Prevalence	Low Performing TPs Prevalence
Market-Linked Skill Development	Frequent	Rare
Employer/Industry Alignment	Frequent	Rare/Generic
Placement as Outcome	Detailed, Structured	Stated, Less Specific
Social Inclusion	Purposeful	Occasional/Mentioned
Holistic Development (soft skills)	Common	Uncommon
Detailed Objectives	Yes	Often Lacking

Q2: Identification of Specific Training Needs

- **High Performing TPs:** Conduct structured needs assessments using surveys, community engagement, employer consultations, and skill gap studies.
- **Low Performing TPs**: Rely on informal methods or general assumptions, with little evidence of systematic or data-driven planning.

Table 4.24: Comparative Table: Identification of Needs Across Groups

Theme/Approach	High Performing TPs (Prevalence)	Inefficient TPs (Prevalence)
Formal Needs Assessments/Surveys	Frequent	Rare
Employer/Industry Consultation	Frequent	Infrequent
Data-Driven/Skill Gap Studies	Frequent	Rare
Focus Groups/Community Engagement	Common	Occasional
Market Research (detailed)	Frequent	Rare or briefly mentioned
Short/Generic Responses	Less Common	More Common

Q3: Mobilization Challenges and Strategies

- Both groups report challenges such as low awareness and socio-cultural resistance.

- **High Performing TPs**: Describe proactive, community-based outreach strategies, including counselling and localized engagement.
- **Low Performing TPs:** Offer vague descriptions with fewer concrete or multi-layered strategies.

Table 4.25: Comparative Table - Response Characteristics

Aspect	High Performing TPs	Low Performing TPs
Challenge Description	Specific and detailed	Generic and brief
Local Engagement	Frequent and multi-level	Infrequent/occasional
Solutions Described	Multi-step and proactive	Often single-step/generic
Counselling/Guidance Involvement	Nearly universal and structured	Universal but less described
Framing of Barriers	Problems to be solved	Often as immutable obstacles

Q4: Counselling Practices

- Universally acknowledged across both groups.
- **High Performing TPs**: Detail regular, structured counselling conducted by trained staff, focused on motivation and retention.
- **Low Performing TPs**: Mention counselling generally, with limited elaboration on frequency, delivery, or personnel

Table 4.26: Comparative Table - Counselling Practices

Counselling Practice Aspect	High Performing TPs	Low Performing TPs
Universal Availability	Yes (100%)	Nearly all (100%)
Detail & Structure	High	Lower
Designated/Trained Personnel	Often emphasized	Sometimes specified

Counselling Practice Aspect	High Performing TPs	Low Performing TPs
Focus on Holistic Support & Motivation	Common	Less common
Frequency/Ongoing Sessions	Frequently described as regular	Rarely described
Counselling Tag Marked	28/28 (100%)	14/14 (100%)

Q5: Challenges in Delivering Training Effectively

- **High Performing TPs**: Face challenges like attendance or motivation, but often pair them with remedial actions.
- **Low Performing TPs:** Report higher dropouts and infrastructure issues, with fewer strategies described for addressing them.

Table 4.27: Tag Analysis and Quantitative Difference

Challenge Tag	High Performing TPs (n=28)	Low Performing TPs (n=14)
Drop-Out	6	11
Training Delivery (attendance/server)	7	8
Infrastructure	3	4
Trainee Motivation/Candidate Aspiration	2	3

Table 4.28: Main Challenge Pattern

Aspect	High Performing TPs	Low Performing TPs
Attendance/Dropout	Common, often linked to trainee side & proactive tone	Very common; linked to payment/operation/systemic barriers
Infrastructure/Technology	Sometimes present, less dominant	Frequently mentioned, often externalized
Motivation/Education Barriers	Cited, especially for marginalized/low-literacy candidates	Cited, but with less detail or context

Aspect	High Performing TPs	Low Performing TPs
Proactivity	Regular efforts to remedy issues	Rarely any mention of remediation
Response Detail	Specific and elaborative	Often short, problem-listing

Q6: Alignment Between Training Content and Job Market Needs

- **High Performing TPs:** Demonstrate strong market alignment through industry consultation, curriculum updates, and hands-on exposure.
- **Low Performing TPs**: Make broad claims of alignment but provide limited evidence of active engagement with labour market demands.

Table 4.29: Summary Table

Practice/Theme	High Performing TPs	Low Performing TPs
Routine market analysis	Frequently described	Rarely described
Employer/industry input	Common, detailed	Occasionally, brief
Syllabus/curriculum update	Detailed, continuous	Occasionally mentioned
Practical/industry exposure	Common	Available, less detailed
Tag prevalence ("Market Linked")	64%	50%

Q7: Trainer Roles and Recruitment

- **High Performing TPs:** Emphasize qualifications, relevant experience, and continuous professional development of trainers.
- **Low Performing TPs:** Focus on minimum compliance, SOPs, and recruitment norms, with less emphasis on trainer quality or upskilling

Table 4.30: Tag Prevalence Comparison

Aspect	High Performing TPs	Low Performing TPs
Trainer Role Tag (at least once)	6	10
Trainer Recruitment Tag (at least once)	13	7

Table 4.31:Observed Pattern

Dimension	High Performing TPs	Low Performing TPs
Trainer's Quality Role	Detailed, multifaceted	Recognized, less detail
Recruitment Process	Clear, multi-step (qualifications, TOT, demo)	Often just interview/document check
Ongoing Training/Workshops	Frequently mentioned	Seldom mentioned
Industry Linkage in Recruitment	Sometimes highlighted	Seldom highlighted
SOP/Compliance Reference	Sometimes	Frequent
Tag Prevalence (Role)	Lower (often less explicit)	Higher (often cited as challenge)

Q8: Seeking Feedback from Trainees

- Almost universal across providers.
- **High Performing TPs**: Use feedback for curriculum refinement, trainer evaluation, and quality assurance
- **Low Performing TPs**: Collect feedback but rarely describe its application or follow-up mechanisms.

Table 4.32: Comparative Table - Feedback Collection

Dimension	High Performing TPs	Low Performing TPs
Prevalence	Near-universal	Near-universal
Detail/Process	Frequently described, structured	Often terse, minimal detail

Dimension	High Performing TPs	Low Performing TPs
Use of Feedback	Quality improvement, curriculum adjustments, trainer evaluation	Seldom specified or not mentioned
Feedback Tag Marked	96%	93%

Q9: Support for Female Trainees

- Both groups mention safety and schedule flexibility.
- **High Performing TPs**: Go further—offering mentorship, leadership opportunities, and gender-sensitive interventions.
- **Low Performing TPs**: Responses are often brief or compliance-focused

Table 4.33: Summary Table: Support Practices for Females

Support Aspect	High Performing TPs	Low Performing TPs
Safe environment/facilities	Frequent, detailed	Occasional, generic
Mentorship/motivation	Common	Rare
Parental/Guardian engagement	Often described	Rarely mentioned
Flexible scheduling	Frequent	Sometimes
Placement/career support	Often highlighted	Occasionally mentioned
Tag prevalence (any "1")	25/28 (89%)	13/14 (93%)

Q10: Support for Minorities (SC/ST/OBC)

- Both groups acknowledge inclusion mandates
- **High Performing TPs**: Engage in active mobilization, targeted counselling, and scholarship support.
- **Low Performing TPs:** Mostly reference policy adherence, with few examples of targeted outreach

Table 4.34: Summary Table: Support for Marginalized Groups

Support Aspect	High Performing TPs	High Performing TPs
Equal access stated	Frequently, in detail	Often, but brief
Special mobilization efforts	Common	Rare/occasional
Scholarships/benefits	Sometimes mentioned	Rare
Policy/SOP reference	Occasional	More frequent
Tag prevalence (any "1")	26/28 (93%)	13/14 (93%)

Q11: Challenges in Ensuring Inclusivity

- Common across groups: Socio-economic constraints, education gaps, and cultural resistance.
- **High Performing TPs**: Frame challenges as solvable, with detailed strategies to address them
- **Low Performing TPs**: Focus more on systemic limitations, often with less optimism or initiative

Table 4.35: Summary Table - Challenges in ensuring inclusivity

Challenge Type	High Performing TPs	High Performing TPs
Socioeconomic/Cultural	Frequent & detailed	Occasional
Educational gaps	Frequent	Rare
Operational/admin hurdles	Rare	More frequent
Framing as surmountable	Common	Less common
Detail of strategy	More detailed	More general

Q12: Tie-ups or Partnerships with Employers for Student Placements

- **High Performing TPs:** Report ongoing, active partnerships with named sectors and employers; describe the nature of engagement.
- **Low Performing TPs**: Refer to partnerships vaguely or mention them infrequently

Table 4. 36: Comparative Overview

Aspect	High Performing TPs	Low Performing TPs
Partnerships stated	Nearly all	Majority
Detail in narrative	Frequent, some sector/firm naming	Rare, mostly "Yes/No"
Ongoing engagement	Often mentioned	Infrequent
Tag prevalence	High	Moderate

Q13: Perception of Placement Rate as an Indicator of Training Quality

- **High Performing TPs**: View placement as one of several quality indicators, linking it to relevance and employer feedback.
- **Low Performing TPs:** Often question the value of placement metrics or attribute low rates to external, uncontrollable factors

Table 4.37: Key Differences - Perception of Placement Rate as an Indicator of Training Quality

Point of Reflection	High Performing TPs	Low Performing TPs
Explicit link to quality	Common	Sometimes, less detail
Mention of limitations	Frequent, nuanced	Sometimes
Quality assurance focus	Often referenced	Rarely described
Tag prevalence ("Placement Focus")	High	High

Q14: Key Indicators of an Efficient Training Program

- **High Performing TPs**: Mention engagement, placement success, curriculum relevance, continuous improvement, and use of feedback.
- **Low Performing TPs**: Focus more on regulatory compliance and output targets like placement numbers, without qualitative depth

Table 4.38: Summary Table - Key Indicators of an Efficient Training Program

Indicator	High Performing TP	Low Performing TP
Placement rates	Frequently cited	Frequently cited

Indicator	High Performing TP	Low Performing TP
Trainee engagement/satisfaction	Common, with detail	Occasionally, less detail
Industry/curriculum alignment	Detailed, routine reference	Rarely explicit
Quality assurance/feedback mechanisms	Systematic	Seldom systematic

Q15: Major Challenges in Student Placement After Training

- **High Performing TPs:** Identify the scarcity of local job opportunities, candidate reluctance to migrate for work, and unrealistic salary expectations as primary barriers to successful placement.
- **Low Performing TPs:** Emphasize similar issues around relocation and expectations but also highlight additional challenges such as administrative delays, documentation issues, and gaps in employment readiness among train

Table 4. 39: Comparative Table - Challenges in Placement

Challenge Theme	High Performing TPs	Low Performing TPs
Lack of Local Opportunities	Frequent	Frequent
Reluctance to Relocate/Travel	Frequent	Frequent
High Salary/Job Role Expectations	Common	Common
Employer/Documentation Issues	Occasionally Noted	More Often Noted
Drop-outs post-placement	Regularly Reported	Present
Administrative Hurdles	Less Frequent	Frequently Reported
No Major Challenge	Few Respondents	Few Respondents

Q16: Other Significant Challenges or Issues

- **High Performing TPs:** Discuss sectoral issues like rural-urban divides, infrastructure gaps, and shifting industry expectations.
- **Low Performing TPs**: Highlight administrative delays, stipend disbursement issues, and operational inefficiencies

Table 4.40: Common Challenge Theme - Other Significant Challenges or Issues

Challenge Aspect	High Performing TPs	Low Performing TPs
Rural-urban infrastructure	Common	Less common
Administrative delays	Sometimes	Very common
Motivation/awareness	Mentioned	Common
Technology/process issues	Less common	Frequently cited
Need for sector/industry link	Sometimes	Occasionally

4.3.2 Thematic Analysis of Trainee Responses

To understand the lived experiences and satisfaction levels of individuals who completed skill training programs, the study conducted a telephonic survey with certified trainees. Out of 233 individuals contacted, 113 provided complete responses, resulting in a response rate of approximately 48.5% (Taherdoost & Madanchian, 2024).

This level of participation lends confidence to the representativeness of the feedback collected, while also reflecting the practical realities of field-based qualitative research, where partial responses, refusals, or inaccessibility are not uncommon. To enhance inclusivity and respondent comfort, researcher conducted follow-ups and provided clarifications where needed, fostering a respectful and responsive interaction throughout the data collection process.

Table 4.41: Certified Trainee Survey Sampling, Respondent Demographics, and Response Rate

Parameter	Description/Value
Total trainees attempted (targeted)	233
Total responses received (complete)	113
Response rate	48.50%
Survey period	Feb 2024 to March 2025
Survey mode	Tele-calling (Hindi/Bengali; follow-ups as needed)
Gender (n, %)	Male: [23, 20.35%], Female: [88, 77.88%]

Parameter	Description/Value
Total trainees attempted (targeted)	233
Provider type (%)	Center Based: [67]59.29%, Industry-Integrated: [46]40.71%
Efficiency group (%)	High Performing (PTE ≥ 0.85): [69] 61.06%, Low Performing (PTE < 0.85): [44] 38.93%

a. **Likert-Scale Ratings: Overview**

Trainees rated their experience with trainers, the quality of the training, and the adequacy of facilities using a 0–5 scale. The results were stratified by whether the TP was classified as High Performing (PTE ≥ 0.85) or Low Performing (PTE < 0.85).

Table 4.42: Likert Scale Ratings Overview

Outcome Area	Mean (High Performing TP)	Median (High Performing TP)	Mean (Low Performing TP)	Median (Low Performing TP)	Standard Deviation (High Performing TP)	Standard Deviation (Low Performing TP)
Trainer Quality	4.9	5	4.93	5	0.46	0.29
Training Satisfaction	4.93	5	4.91	5	0.37	0.38
Facility Satisfaction	4.81	5	4.71	5	0.62	0.67

- Both groups report extremely high satisfaction, with most responses at the ceiling value of 5.
- Variability in scores is low, and no statistically significant group differences were found.

Ceiling Effect Consideration

Descriptive analysis showed 98 of 113 trainees (≈ 87 %) chose the top score 5 on the Trainer Quality, 104 of 113 (≈ 92 %) did so on Training Satisfaction, and 101 of 113 (≈ 89 %) on facility satisfaction. This ceiling is expected in government-funded short-term programmes whose primary objective is to meet minimum service standards rather than create fine-grained differentiation in learner sentiment. Because (i) satisfaction scores were used only for contextual interpretation, not as inputs to the DEA frontier or the Tobit regression; (ii) the ceiling pattern was nearly identical across high performing and low performing TP groups (median = 5, IQR = 0); and (iii) open-ended comments supplied qualitative nuance, no additional censored-data techniques were applied. Hence the high scores are treated as a substantive finding—indicating broad learner approval—rather than a statistical artefact requiring adjustment.

b. Thematic Analysis of Open-Ended Comments

All verbatim themes, frequencies, and sample phrases below are drawn directly from the dataset responses.

b.1 Trainer Quality and Conduct

Positive Feedback—Predominant in Both Groups:

- "The trainer was very helpful and always responded to our queries."
- "The trainer was really good and he taught us brilliantly."
- "Their behaviour and teaching methods were good."
- "The teaching methods of the trainers were very simple and easy to understand."
- "Teacher was very good. He was patient enough and kind."

Less Frequent Critique:

- "As the trainer was very irregular and he used to inform us very late that he won't come."

- “Not satisfying. Trainers were keep being changed, they had some behavioural issue and they were not available every time as well. I would rate 1/5.”

Table 4.43: Trainer Quality and Conduct

Feedback Theme	High Performing TPs	Low Performing TPs
Helpful, patient	Frequent	Present
Trainer absent/irreg.	Present (rare)	Present (rare, a bit more often)
Behavioural Issues	Rare	Rare

b.2 Training Experience

Positive Highlights:

- “I learnt stitching in-depth which is helping me to run my business.”
- “I learnt the concepts in depth and the process was very smooth.”
- “They taught me well. their teachings skills were clear and easy to understand”

Noted Issues:

- “Whenever they were available, they taught us properly. So, I will rate the training 2.”
- “As I said earlier, they were not teaching us in-depth about the makeup or the product.”

b.3 Training Facility and Equipment

Positive Feedback:

- “The machines were in good condition.”
- “Infrastructure and facilities of the institute was very good.”

- “All the computers were in good condition.”

Concerns about Equipment:

- “Majority of the computers were in bad condition... although the trainer and the institute replaced those computers after we complaint about it.”
- “The machines were working but sometimes it wasn't working properly.”
- “There was a lack of machines per students. Some of us had to adjust with each other.”

b.4. Job Preparedness, Additional Challenges, and Discrimination

Table 4.44: Job Preparedness, Additional Challenges, and Discrimination

Theme	Number/Proportion	Representative Examples
Yes, well-prepared	Vast majority	“Yes, I got a Data Entry job…”
		“Yes, they did prepare me well…”
Uncertain/Don’t know	Few	“Don’t know.”
No/Not exactly	Sparse	“Not exactly. Though some companies came for placement interviews, I didn’t get a job from there.”

b.5 Other Challenges During Training

Table 4. 45: Other Challenges During Training

Challenge Type	Frequency in Data	Representative Examples
No/None	Most responses	“No”
Equipment/facility issues	Occasional	“Majority of the computers were in bad condition... although… replaced.”
Trainer/systemic issues	Few	“Sometimes the trainer was absent…”
		“Not satisfying. Trainers were being changed…”

Challenge Type	Frequency in Data	Representative Examples
Class size/attention	Rare	“Full class with only one teacher, so… problem solving.”
Job/placement-specific	Occasional	“Didn’t get a job after that. It didn’t help me.”

b.6 Discrimination

Table 4.46: Discrimination

Response Type	Count/Prevalence	Representative Examples
No	Nearly universal	“No”
Maybe/Can’t say	1–2 respondents	“Maybe”, “Can’t say”
Yes	None	—

c. Overall Patterns and Summary

- **High satisfaction dominates** both Likert scores and qualitative comments, regardless of the efficiency group.
- **Positive experiences**—especially regarding trainers and learning outcomes—are richly described and are present everywhere.
- **Negative/critical feedback** is limited and scattered: most issues relate to occasional trainer absence, equipment shortfall, or crowded classes.
- **Perceived job preparedness** is high, though some trainees note limited placements despite feeling ready
- **Additional challenges** are minor and most often involve infrastructure or occasional trainer irregularity.
- **Discrimination is almost never reported**

d. Tables Summary

Table 4.47: Summary of Key Themes and Sample Comments

Aspect	High Performing TP Example	Low Performing TP Example
Trainer	"The trainer was very helpful and always responded..."	"Their behaviour and teaching methods were good."
		"Sometimes the trainer was absent..."
Training	"I learnt the concepts in depth and process was smooth."	"They were not teaching us in-depth about the makeup or product."
Facilities	"All machines were in good condition."	"Majority of the computers were in bad condition... replaced after complaint."

This section demonstrates that certified trainees, both from high performing and low performing TPs, overwhelmingly report positive experiences across the domains of trainer quality, training experience, and facilities. There are infrequent but actionable mentions of trainer irregularity and equipment shortages, and discrimination is absent. The findings indicate strong overall program satisfaction, while also revealing operational nuances that provide valuable insights for quality assurance and ongoing improvement.

4.4 Summary

This chapter presents a comprehensive mixed-methods analysis of 134 government-sponsored skill training providers in West Bengal, integrating quantitative techniques—including Data Envelopment Analysis, K-means clustering, and Tobit regression—with qualitative thematic analysis of provider and trainee narratives. The findings reveal significant operational variability across providers. While many operate close to their optimal scale, technical efficiency remains uneven, highlighting considerable room for improving how inputs are translated into outputs.

Efficient training providers distinguish themselves through structured practices: they conduct formal market needs assessments, offer systematic counselling, maintain active industry partnerships, and implement purposeful inclusion strategies. In contrast, less efficient providers tend to rely on generalized, reactive approaches with limited evidence of strategic planning or alignment to labour market needs.

Trainee feedback—though largely positive across the board—suggests that both high and performing TPs are associated with deeper learning experiences, better equipment usage, and stronger job readiness. However, this does not always correspond to higher satisfaction scores, indicating that subjective experience may be influenced by factors beyond operational quality.

The analysis underscores that management practices, rather than just scale or inputs, play a central role in shaping efficiency. Notably, training centers with greater gender diversity tend to perform more efficiently, reinforcing the value of inclusive design. Peer benchmarking further reveals internal exemplars—efficient providers that can serve as role models for system-wide improvement.

Altogether, Chapter 4 connects technical efficiency findings with real-world organizational behaviors, offering actionable insights for policymakers, administrators, and practitioners seeking to strengthen the effectiveness and equity of India's skill development ecosystem.

CHAPTER 5: RESULTS, DISCUSSIONS & CONCLUSION

5.1 Introduction

This chapter presents the integrated results of the quantitative efficiency analysis (Data Envelopment Analysis, clustering, Tobit regression) and the qualitative thematic analysis of survey responses from training providers and certified trainees. Following an explanatory sequential design, quantitative findings are first summarized and then enriched with qualitative evidence to address the research objectives.

5.2 Results and Discussions

5.2.1 Efficiency Benchmarking via DEA

The efficient DMUs define the empirical “best practice frontier.” Inefficient DMUs (PTE < 1) can be compared against these benchmarks to identify improvement opportunities—both within the same type (peer comparison) and across types (cross-type learning).

5.2.1.1 Global Efficiency Distribution

Of 134 providers, 18% achieved pure technical efficiency (PTE = 1.0) under the output-oriented VRS model. Scale efficiency analysis showed that many providers operated at sub-optimal scale, particularly mid-sized Center-Based TPs.

Table 5.1:Global Efficiency Distribution

DMU Type	Total DMUs	Efficient DMUs (PTE = 1.0)	Efficiency Rate (%)
Industry-Integrated TP	71	18	25.40%
Center based TP	63	6	9.50%

The percentage of efficient DMUs is higher among Industry-integrated TPs (25.4%) than Center based TPs (9.5%), implying that the Industry-integrated DMUs, as a group, are more likely to employ best practices, have more optimized processes, or benefit from operational or contextual factors that better align resources with outputs. Conversely, a smaller percentage of Center-based DMUs achieve full efficiency, suggesting there is more scope for process improvement or that they might face operational challenges not present in Industry-integrated DMUs. A proportions test (chi-square test of independence) was conducted to assess whether the proportion of technically efficient DMUs (PTE=1) differs significantly between Industry-integrated type and Center based type training providers. The Chi square result yielded a chi-square statistic of 4.6625 with a p-value of 0.0308, which is below the conventional threshold of 0.05. This suggests that the observed difference in efficiency rates between Industry-integrated and Center-based DMUs is statistically significant and unlikely to be due to chance.

Tobit Regression: A 10 percentage-point increase in female trainee share predicted a 0.04 increase in PTE ($p < 0.01$). Caste composition (SC/ST/OBC share) was not a significant predictor, suggesting that gender inclusion practices more directly influence efficiency.

5.2.1.2 Efficiency Comparison by Cluster and Provider Type

To verify whether the global efficiency advantage of Industry-Integrated (II) providers holds once like-with-like comparisons are imposed, we examined the DEA results within the three homogenous clusters already created by the K-means procedure (section 4.2.2). After the output-oriented VRS DEA was run separately for each cluster, we compared the proportion of II and Centre-Based (CB) providers that attained full technical efficiency (PTE = 1.00). Table 5.2 reports these within-cluster comparisons.

Table 5. 2: Cluster Insights and Global Insights

Cluster	Industry-integrated DMUs (total)	Industry-integrated Efficient (PTE = 1)	Center-Based DMUs (total)	Center-Based Efficient (PTE = 1)	Efficiency rate Industry-integrated vs Center-Based	Fisher-exact p-value
1	16	5	15	5	31 % vs 33 %	0.694

Cluster	Industry-integrated DMUs (total)	Industry-integrated Efficient (PTE = 1)	Center-Based DMUs (total)	Center-Based Efficient (PTE = 1)	Efficiency rate Industry-integrated vs Center-Based	Fisher-exact p-value
2	23	8	19	5	35 % vs 26 %	0.401
3	32	11	29	2	34 % vs 7 %	0.009
All clusters combined	**71**	**24**	**63**	**12**	**34 % vs 19 %**	**0.0413**
Global DEA	**71**	**18**	**63**	**6**	**25% vs 9.52%**	**0.0142**

- **Cluster 1:** No material difference is observed between the two delivery models Both groups recorded similar efficiency rates (31% vs. 33%), and the Fisher's exact test confirmed the absence of a statistically significant association ($p \approx 0.69$, one-sided). This cluster is characterized by large-scale providers with high enrolments (average ~1,170 candidates), moderate trainer experience, and shorter course durations.

- **Cluster 2:** Industry-Integrated providers exhibited a somewhat higher share of efficient units compared with Centre-Based providers (35% vs. 26%). However, this difference did not reach statistical significance ($p \approx 0.40$, one-sided), suggesting that efficiency outcomes in this cluster—characterised by mid-sized providers—are not strongly differentiated by delivery model.

- **Cluster 3:** A pronounced efficiency advantage was evident for Industry-Integrated providers. Their efficiency rate (34%) was nearly five times higher than that of Centre-Based providers (7%), and the difference was statistically significant (Fisher's exact $p \approx 0.009$, one-sided).

When the clusters are pooled, 34 % of II providers are fully efficient compared with 19 % of Centre-Based (CB) providers (Fisher exact $p \approx 0.041$). The relative-risk estimate indicates that an II provider is roughly 1.8 times more likely to reach the efficiency frontier (95 % CI ≈ 0.97 – 3.25).

In the aggregate efficiency assessment, 25% of Industry-Integrated providers achieved full efficiency compared with only 9.5% of Centre-Based providers. This difference is statistically significant ($\chi^2 = 4.66$, df = 1, $p \approx 0.031$; Fisher's exact $p \approx 0.014$, one-sided), indicating that Industry-Integrated providers are substantially more likely to operate on the efficiency frontier when the full dataset is considered. The relative risk indicates that Industry-Integrated providers were about 2.7 times more likely to attain efficiency than Centre-Based providers reinforcing the systemic advantages of the industry-linked delivery model.

The cluster analysis confirms that the higher efficiency of the Industry-integrated model is not an artefact of input heterogeneity.

5.2.2 Training Provider Feedback

- **Structured Needs Assessment:** High performing training providers consistently use formal surveys, focus groups, and labour-market data to tailor program design. Low performing providers more often rely on ad-hoc or informal methods.

- **Counselling & Feedback Loops:** High-efficiency TPs institutionalize multi-stage counselling (pre-training and during the training) and systematically collect trainee feedback.

- **Employer Partnerships:** High performing Center-based Training providers demonstrate continuous co-creation of training content with industry partners, while less efficient TPs describe one-off or transactional engagements. For II TPs, the curriculum is based on their industry requirements designed in coordination with the council, TET&SD Department whenever required.

- **Inclusion Strategies:** High performing TPs report bespoke support (flexible hours, mentorship) for women and marginalized groups. Low performing TPs also mentioned supporting female and SC/STs or other minority groups. The same is also in concurrence with the trainee feedback where no discrimination was reported.

5.2.3 Certified Trainees Responses

- **Satisfaction Levels:** Trainee ratings for trainer quality, overall training, and facilities averaged above 4.8/5 across all provider types and efficiency levels, with no statistically significant differences.

- **Qualitative Feedback:** Trainees who passed out from high performing TPs offered richer, more detailed praise (e.g., consistent trainer availability, in-depth instruction), while those of low performing TPs noted equipment issues and trainer irregularity (although not frequently).

High baseline satisfaction indicates that program standards meet minimum quality thresholds across the sector. However, more elaborate positive narratives and among high performing TP trainees reinforce the concrete benefits of structured practices and systematic approaches identified in the provider analysis.

5.4 Meta Inferences

This section synthesizes all key findings from the comparative efficiency assessment of short-term skill training providers, integrating quantitative benchmarks from DEA, qualitative insights from training providers, and ground-level perspectives from certified trainees. This triangulation directly addresses the research objectives:

- Benchmarking best practices via efficiency frontiers

- Understanding how efficient models can be upscaled

- Charting actionable pathways for inefficient providers to improve

5.4.1 Comparative Efficiency of Provider Types

The efficiency comparison between Industry-Integrated (II) and Center-Based (CB) training providers highlights the structural strengths of industry-led delivery models.

At the cluster level, results were mixed. In Cluster 1 (large-scale providers with high enrolments and shorter courses), efficiency outcomes were almost identical across models, suggesting that sheer scale may neutralize the advantages of industry integration. In Cluster 2 (mid-sized providers), II providers recorded a higher proportion of efficient units (35% vs. 26%), but the difference was not statistically significant, implying that sectoral mix or candidate profile may be stronger determinants of efficiency in such contexts. In Cluster 3 (smaller, resource-constrained providers), II providers displayed a clear and statistically significant advantage, underscoring the importance of embedded industry resources when institutional capacity is otherwise limited.

At the global DEA level, the evidence was more robust: 25% of II providers reached the efficiency frontier compared with 9.5% of CB providers, a statistically significant difference ($\chi^2 = 4.66$, $p \approx 0.031$). The relative risk estimate (RR = 2.66; 95% CI: 1.13–6.29) indicates that II providers were about 2.7 times more likely to be efficient overall.

These results reflect the inherent strengths of Industry-Integrated models. Unlike CB providers, II providers are embedded within functioning industries, meaning that:

- **Trainers are active industry professionals**, equipped with up-to-date, practical expertise.
- **Equipment and training infrastructure are the same as those used in production settings**, eliminating the gap between training and workplace requirements.

- **Workplace exposure is intrinsic**, as training occurs in real industrial environments, reducing the disconnect often found in classroom-based delivery.

The efficiency gains observed in Industry-Integrated providers stem from the fact that trainees learn within functioning industry environments, using the same equipment and guided by professionals who are active in the field. This exposure allows candidates to become familiar with workplace practices and expectations even before formal employment begins. In contrast, Center-Based providers must approximate industry conditions through classroom simulations, limited training resources, or borrowed infrastructure. As a result, trainees from CB settings often face a steeper adjustment when transitioning to real jobs, which may reduce overall efficiency and placement effectiveness.

From a policy standpoint, the findings suggest that while II providers inherently operate at an advantage, elements of their model can still be extended to CB providers. These include employing part-time trainers with direct industry experience, investing in modern equipment that mirrors workplace conditions, and increasing opportunities for trainees to engage in on-the-job learning. Such adaptations could help CB providers narrow the efficiency gap and make the overall skill ecosystem more productive.

5.4.2 Best Practice Benchmarks

The application of output-oriented, Variable Returns to Scale DEA identified a benchmark set of high-performing providers (PTE ≥ 0.85) and highlighted substantial scope for improvement among the remaining pool. The peer benchmarking is also presented in section 4.2.4. While both Center-Based and Industry-Integrated providers had efficient performers, Industry-Integrated providers demonstrated a significantly higher likelihood of achieving efficiency, underscoring the advantages of industry alignment in driving outcomes.

Drawing on a detailed review of qualitative responses and efficiency scores, this section presents ten best practices that characterize high-performing training providers (PTE ≥ 0.85) in skill development programs. It directly addresses the research objective of distilling best practices from the most efficient TPs and formulating actionable guidelines for the Government and training partners to uplift under-performing providers.

1. Structured Needs Assessment

- Conducting baseline surveys, skill gap studies, and labour market analyses to design programs aligned with actual job market requirements.
- Regular consultation with employers, industry bodies, and community stakeholders to validate and updating/co-creating training content.

Reflecting Deming's PDCA "Plan" phase, systematic needs assessment underpins continuous improvement loops.

2. Multi-Channel Candidate Mobilization

- Employing diverse outreach techniques such as door-to-door campaigns, local meetings, and career guidance camps.
- Engaging community influencers, self-help groups, and panchayat members for trust-building and reach.

3. Professionalized Counselling Support

- Delivering structured, multi-stage counselling before and during the training.
- Utilizing trained counsellors, career guidance experts, and soft skills trainers to address both professional and personal development needs.
- Motivating the candidates to join the workforce post training

4. Robust Employer Partnerships

- Building formal partnerships with employers for placements, curriculum co-creation, and ongoing job-market intelligence.
- Maintaining regular dialogue with industry to match training with evolving sectoral needs and opportunities.

5. Comprehensive Trainee Feedback Systems

- Soliciting regular feedback through structured forms, meetings, and direct discussions.
- Using feedback systematically for program improvement, and addressing participant concerns.

6. Targeted Inclusion and Support Measures

- Implementing gender-sensitive training schedules, safe infrastructure, and tailored support for female trainees and marginalized groups.
- Organizing special motivational, leadership, and empowerment workshops.

7. Rigorous Trainer Recruitment and Development

- Recruiting trainers with relevant qualifications, industry experience, and teaching skills.
- Providing ongoing professional development, training-of-trainers (TOT), and orientation sessions to ensure trainers stay up-to-date.

8. Proactive Strategies for Dropout and Attendance

- Identifying root causes of absenteeism through regular monitoring and personalized support.
- Involving guardians, delivering motivational sessions, and implementing flexible learning options when needed.

9. Quality and Outcome-Driven Program Management

- Tracking key indicators such as placement rates, trainee satisfaction, and employer feedback as routine measures of program success.
- Carrying out regular internal reviews and process audits to sustain and improve the efficiency and relevance of offerings

10. Enhanced Placement Support and Mentorship

- Continuous mentoring and motivation for candidates to accept employment opportunities after training
- Guidance on the practical realities of workplace entry, including industry expectations, workplace culture, and adaptation challenges
- Emphasis on communicating the long-term benefits of sustained employment for both personal growth and career progression

These best practices—grounded in data, employer engagement, inclusivity, and continuous improvement—enable high performing training providers to deliver skill programs that are both market-relevant and socially responsive.

5.4.3 Perceptions on Placement as Measure of Training Quality

Placement rates are routinely used by policymakers, funders, and administrators as a primary indicator of skill training program effectiveness. While securing employment for trainees is a key policy goal, there is ongoing debate in education literature about whether placement statistics alone can accurately capture the breadth and depth of training quality. To explore this, training providers (TPs) in this study were directly asked if they believe placement rates reflect true training quality.

Several TPs expressed reservations about equating placement numbers with training quality. Their perspectives highlight the complexity and multidimensional nature of short-term training outcomes. Three main themes emerged:

1. **Influence of External Factors**

    - Many TPs noted that job availability in the local market, industry demand, and trainees' willingness to relocate significantly impact placement outcomes—regardless of training quality
    - Several trainees opt not to take up jobs because they are reluctant to leave their home districts. For some, the primary motivation for enrolling in training is to gain certification or personal skill development rather than immediate employment, which shapes how placement statistics should be interpreted

2. **Training Outcomes Beyond Immediate Employment**

    - Providers stressed that trainees may benefit in ways not visible in short-term placement numbers—such as increased self-confidence, business creation, or further education.

3. **Placement Rates as an Incomplete or Misleading Metric**

- Some TPs argued that while placement is important, it can be misleading—high rates do not always signal job sustainability, satisfaction, or genuine skill gain.

Interpretation

While placement rates remain an important metric, many providers caution against using them as the sole or definitive measure of training quality. Quality, according to these TPs, should be assessed with a broader lens: considering skill acquisition, feedback from employers and trainees, longer-term retention or career advancement, and socio-economic constraints faced by the youth in various localities.

Integration with DEA and Qualitative Findings

Notably, some highly efficient (DEA frontier) TPs also echoed these concerns, reinforcing that high technical efficiency does not automatically guarantee high placement rates—and vice versa—due to factors outside institutional control. Conversely, some inefficient TPs with strong inclusion or community-work profiles cited similar placement constraints, highlighting the limits of single-outcome performance metrics.

5.4.4. Implications for Scaling and Sector Improvement

- **Leverage Industry-Embedded Practices:** Encourage wider adoption of models where trainees gain hands-on exposure in real production settings. Even in CB centers, policies can support part-time trainers from industry, shared-use of industrial equipment, and stronger integration of workplace routines into training delivery

- **Adopt Structured Routines:** Policy and institutional support should focus on widespread adoption of systematic needs assessment, regular curriculum revision, professionalized counselling, and routine feedback collection.

- **Facilitate Peer Learning:** Create platforms for underperforming providers to shadow or collaborate with efficient Industry-Integrated providers, enabling transfer of concrete practices such as trainer utilization, placement support, and workplace orientation.

- **Address Systemic Barriers:** Investments in equipment, trainer capacity, and process efficiency will have cross-cutting benefit for all providers.

This integrated meta-inference demonstrates that high efficiency and satisfaction in skill training provision are fundamentally linked to the depth and consistency of operational practices rather than just provider type or simple policy adoption. While satisfaction is universally high, the richest, most detailed positive trainee experiences correlate with efficient, systematically managed providers.

5.6 Implications of the Study

The findings from this study offer several practical takeaways that can help improve the effectiveness and inclusivity of the short-term skill training programs:

- **Smarter Policy Decision and Policy Design:** When governments set accreditation standards or decide on funding, they should look beyond just final outcomes. Including indicators like how well a program assesses learner needs or integrates feedback can lead to more responsive and impactful training

- **Boosting Capacity Through Peer Learning:** Creating platforms where high-performing training providers can share their methods with those struggling can help spread best practices. This kind of peer-to-peer learning can speed up the adoption of structured and efficient routines.

- **Encouraging Gender Inclusion:** Offering targeted incentives—such as grants or bonuses—for programs that successfully enroll and support more women can lead to better overall efficiency. These incentives can also help close gender gaps in access to quality training.

- **Building Stronger Sector Partnerships:** Collaboration between public and private players can help address inefficiency and lead to better outcome. For example, shared infrastructure such as labs or equipment pools can make training more accessible and cost-effective across providers. Evidence from Industry-Integrated providers—who naturally leverage industry facilities, trainers, and equipment—shows that such embedded linkages translate into higher efficiency and better outcomes. Extending elements of this model to Center-Based providers could help narrow the performance gap.

5.6.2 Policy Implications

Drawing on both the quantitative and qualitative study, these policy recommendations aim to guide meaningful reforms in short-term skill development programs. The suggestions reflect real-world experiences from both high- and low-performing providers, highlighting practical challenges and innovative solutions.

1. Align Training with Market Needs

- **Make Needs Assessments Mandatory:** Training providers should be required to conduct structured assessments—like labor market surveys and community consultations—to ensure courses match local job demands

- **Encourage Employer Involvement:** Set up formal channels for employers to co-create curricula and provide feedback, helping programs stay relevant to industry trends.

- **Regular Curriculum Updates:** Policies should support routine reviews of course content by industry experts to keep training aligned with evolving job roles.

2. Strengthen Counseling and Trainee Support

- **Professionalize Counseling Roles:** Establish standards for hiring and training counselors, ensuring they can offer comprehensive support throughout the training journey.
- **Make Counseling a Core Function:** Career guidance, motivation, and personal support should be integral to every training program, with regular evaluations to ensure quality.

3. Promote Inclusion for Women and Marginalized Groups

- **Implement Practical Inclusion Measures:** Move beyond policy statements by requiring providers to adopt real solutions—like flexible schedules, safe facilities, and parental engagement—for underrepresented groups.
- **Track and Reward Inclusive Outreach:** Use detailed data (e.g., by gender or caste) to monitor outreach efforts and link funding or recognition to genuine inclusion outcomes.

4. Improve Placement and Post-Training Support

- **Focus on Local and Sector-Specific Jobs:** Encourage partnerships that reflect local job markets and trainees' mobility preferences, promoting realistic and sustainable placements.
- **Support Relocation and Transitions:** Provide guidance and incentives to help trainees relocate when needed, especially those from vulnerable backgrounds.

5. Focus on Continuous Quality Improvement

- **Use Trainee Feedback Effectively:** Make it mandatory for providers to collect and act on feedback, using it to drive real improvements.
- **Conduct Holistic Reviews:** Encourage mixed-method evaluations—including input from employers and alumni—to define and measure quality beyond just placement numbers.

6. Celebrate Process Excellence

- **Showcase Best Practices:** Highlight successful outcomes of implementing effective needs assessments, counseling, inclusion efforts, and employer engagement
- **Enable Peer Learning:** Offer training and networking opportunities so that struggling providers can learn from successful ones.

7. Redefine Efficiency in Terms of Impact

- **Balance Efficiency with Equity:** Avoid focusing solely on numbers; ensure policies also support programs that serve high-barrier populations and deliver long-term benefits.
- **Broader Success Metrics:** Encourage providers to track and report on job quality, wage progression, career advancement, and social empowerment alongside technical efficiency
- **Recognize Placement as a Choice:** Placement outcomes should account for the fact that many trainees are unwilling to relocate outside their districts, and some pursue training primarily for certification or personal development rather than immediate employment. Efficiency frameworks must therefore reflect both labor-market absorption and the diverse motivations of trainees.

5.7 Major Recommendation

1. **Standardize Needs Assessment Protocols:** Introduce mandatory, periodic labour market studies and community consultations for all training providers to ensure programs are aligned with real-world demand.

2. **Institutionalize Counselling Services:** Require training centers to appoint certified counselors and implement structured counseling modules both before and during the training period, ensuring consistent support for trainees.

3. **Formalize Employer Advisory Boards:** Ensure every training provider maintains an active industry partnership council, enabling regular input from local employers on curriculum relevance and job market trends.

4. **Revamp Infrastructure Funding Models:** Establish pooled funding mechanisms to support equipment upgrades and infrastructure improvements, especially in under-resourced regions.

5. **Support Scale Efficiency for Smaller Providers:** Offer targeted technical assistance to providers operating below optimal scale, including guidance on cohort sizing, resource planning, and operational efficiency.

5.8 Limitations of the Study

While the study offers valuable insights, several limitations should be acknowledged:

- **Sample-Dependent Efficiency Scores**

  The Data Envelopment Analysis results are relative to the sample of training providers in West Bengal. Including providers from other regions or newer entrants could shift the efficiency frontier and alter comparative scores.

- **Cross-Sectional Design Constraints**

The study relies on a single time-point analysis, limiting the ability to assess changes in efficiency or productivity over time.

- **Trainee Survey Ceiling Effects**

  The use of high Likert-scale ratings in trainee feedback may mask subtle differences in quality, making it harder to detect marginal improvements.

5.9 Scope for Future Research

To build on the current findings, future research could explore the following directions:

- **Longitudinal DEA Analysis:** Apply Malmquist indices to track changes in productivity and efficiency over time, capturing the impact of process improvements.
- **In-Depth Case Studies**: Conduct ethnographic research on high-performing training providers to uncover tacit operational routines and cultural factors driving success.
- **Cost-Efficiency Evaluation:** Extend the DEA framework to include financial inputs, enabling a more comprehensive assessment of cost-effectiveness.
- **Experimental Policy Pilots:** Design and test structured interventions—such as mandatory counselling services or employer advisory boards—through randomized controlled trials to evaluate their impact on provider efficiency.

5.10 Conclusion

This chapter addressed the core research objectives of the study by combining quantitative efficiency analysis with qualitative insights. First, the application of DEA enabled the identification of efficiency frontiers across clusters, thereby benchmarking the best-performing training providers. These frontiers not only highlighted the extent of inefficiency but also offered concrete peer references against which underperforming providers could be compared.

Second, the comparative analysis between Industry-Integrated (II) and Center-Based (CB) providers revealed clear differences in efficiency distributions. While the results were not significant across all clusters, the pooled and global DEA findings confirmed that II providers are substantially more likely to reach the efficiency frontier. This establishes the II model as the more productive delivery approach, with features that can be scaled or adapted to strengthen the CB model.

Third, the qualitative findings distilled best practice benchmarks that cut across provider types. Practices such as structured counselling, systematic feedback collection, and inclusive outreach were consistently reported among efficient providers. When aligned with DEA benchmarks, these insights generated a set of actionable guidelines for both government agencies and training partners seeking to uplift weaker providers.

Finally, the integration of evidence from both quantitative and qualitative strands informed a set of policy and practice guidelines. These recommendations are tailored to address systemic inefficiencies and resource gaps while also offering strategies for scaling short-term skill training programs in a sustainable manner.

Taken together, the findings presented in this chapter directly address the research objectives by benchmarking efficiency, identifying comparative advantages between delivery models, distilling best practices, and generating actionable recommendations.

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APPENDIX

1. Reading the Efficiency Frontier Graphs

An efficiency frontier graph is simply a way of showing who is making the best use of their resources. On the graph, the horizontal axis shows one input (for example, course duration), and the vertical axis shows the output (for example, number of trainees certified). The curved line at the top – the frontier – is formed by those training providers who are getting the maximum possible output for the amount of input they use. Any provider shown on the line is efficient, while those below the line are less efficient because they achieve fewer results than the best performers using the same input. The gap between a provider and the frontier represents the scope for improvement.

Since this study considers three inputs and one output, it is not feasible to depict the full production possibility set within a single two-dimensional graph. To address this, separate efficiency frontier plots are constructed, each comparing the output against one input at a time while holding the others aside. These individual plots provide a visual approximation of performance patterns, allowing readers to see how decision-making units (DMUs) fare in different input–output relationships. However, it is important to note that the DEA model itself simultaneously incorporates all inputs and outputs in determining technical efficiency; the 2D frontiers serve only as an illustrative tool rather than a complete representation of the multidimensional efficiency frontier.

2. Reading the Peer Network Diagrams

A peer network diagram provides a visual representation of the reference relationships generated through DEA. In such a network, each node represents a decision-making unit (DMU), while the directed arrows point from inefficient DMUs to the efficient peers that serve as their benchmarks. The thickness of the arrows reflects the λ-weights (peer weights), indicating the relative importance of each reference unit in constructing the efficiency target for an inefficient DMU. Efficient DMUs therefore appear as central nodes with multiple incoming arrows, signifying their frequent role as best-practice benchmarks, whereas inefficient DMUs are positioned as sources pointing outward toward their peers. By examining the network structure, one can identify which providers consistently define the efficiency frontier and which rely heavily on peer references, offering insights into the benchmark centrality and the dominance of certain operational models within the cluster.

Training Provider/ Training Center Basic Details

I am a PhD researcher at ICFAI University. I am currently conducting research focused on efficiency assessment of skill training providers across the state of West Bengal. As a skill training center, your valuable insights and experiences are crucial to the success of this research. I would be deeply grateful if you would consider contributing by completing a brief questionnaire. The questionnaire aims to gather perspectives on general area like the current training practices, challenges faced, and outcomes observed.

The data collected will be used solely for academic research purposes and will be anonymized to ensure the confidentiality of your responses.

* Indicates required question

Email *

Cannot pre-fill email

Training Center Districts you are operating in *

- [ ] ALIPURDUAR
- [ ] BANKURA
- [ ] BIRBHUM
- [ ] COOCHBEHAR
- [ ] DAKSHIN DINAJPUR
- [ ] DARJEELING
- [ ] HOOGHLY
- [ ] HOWRAH
- [ ] JALPAIGURI
- [ ] JHARGRAM
- [ ] KALIMPONG
- [ ] KOLKATA
- [ ] MALDAH
- [ ] MURSHIDABAD
- [ ] NADIA
- [ ] NORTH 24 PARGANAS
- [ ] PASCHIM BARDHAMAN
- [ ] PASCHIM MEDINIPUR
- [ ] PURBA BARDHAMAN
- [ ] PURBA MEDINIPUR
- [ ] PURULIA
- [ ] SOUTH 24 PARGANAS
- [ ] UTTAR DINAJPUR
- [ ] Other:

Name of the Training Provider/Center with TP code and TC Code *

Your answer

Number of Administrative Staff per training center per district. Please mention the TC district wise administrative staff.(excluding the trainers) *

Your answer

Type of Training Center *

- ○ Industry-Integrated TPs
- ○ Center-Based TP
- ○ DDUGKY

Institutional Practices and Efficiency

What are the primary objectives of your training programs? *

Your answer

How do you identify the specific training needs of the target groups you serve? *

Your answer

Do you face any challenge in mobilizing candidates? If yes, how do you tackle the same. *

Do you conduct counselling sessions for your candidates? If yes, who conducts the sessions. *

Your answer

What challenges do you face in delivering training effectively? *

Your answer

How do you ensure alignment between training content and current job market needs? *

Your answer

What role do your trainers play in maintaining the quality of training? How are they recruited and trained? *

Your answer

Do you seek feedback from trainees on the quality and relevance of the training?

- Yes
- No

Inclusivity and Access

How does your institution support female trainees? *

Your answer

How does your institution support minorities, SCs/STs/OBCs *

Your answer

What are the key challenges you face in ensuring inclusivity within your training programs? *

Your answer

Outcomes and Improvements

Do you have tie-ups or partnerships with employers for student placements? *

- Yes
- No

Do you feel your placement rates accurately reflect the quality of training provided? Why or why not? *

Your answer

What do you believe are the key indicators of an efficient training program? *

Your answer

What are the major challenges you face in placing your students after they complete the training? *

Your answer

Are there any other significant challenges or issues that you would like to highlight regarding the provision of training in West Bengal? *

Your answer

Certified Trainee Questionnaire

* Indicates required question

Name

Your answer

Training Provider Name

Your answer

What motivated you to enroll in this training program? *

Your answer

Were you working before you joined the training? *

- ◯ Yes
- ◯ No
- ◯ I was self-employed

Are you working currently? *

- ◯ Yes
- ◯ No
- ◯ I am Self-employed

How would you rate your overall experience with the trainers on a scale of 0 to 5. 5 being the best. *

1 2 3 4 5

○ ○ ○ ○ ○

How would you rate your overall experience with the Content on a scale of 0 to 5. 5 being the best.

0 1 2 3 4 5

○ ○ ○ ○ ○ ○

How would you rate your overall experience with the training facilities on a scale of 0 to 5. 5 being the best. *

0 1 2 3 4 5

○ ○ ○ ○ ○ ○

Did you feel the training prepared you adequately for job placement or self-employment? Why or why not? *

Your answer

What difficulties or challenges did you face during your training? *

Your answer

Did you experience any discrimination (as a female/ Specially-abled/Minority) during the training? *

Your answer

Were there any supports that helped you successfully complete the training? *

Your answer

Would you recommend this program to others? *

- Yes
- No

PUBLICATION AND PRESENTATIONS BY THE SCHOLAR IN THE RESEARCH AREA

1. Published a Paper titled “Caste and Gender Disparities in Drop-out from Short-Term Skill Training”, STRAD Research, Volume 12 Issue 6, June 2025
2. Published a Paper titled “Why They Learn: A Thematic Exploration of Enrollment Motivations in Skill Development Programs”, Journal of Emerging Technologies and Innovative Research, Volume 12 Issue 7, July 2025
3. Presented a paper titled “Skill Development Programmes for Successful Digital Transformation: A Pressing Need”, International Conference on "Digital transformation for Sustainable Business Performance" organized by ICFAI University, Jharkhand in March 2023
4. Presented a paper titled “Intersecting Aspirations: A Gender and Caste based analysis of Motivational Drivers for Enrolling in Short-Term Skilling”, International Conference Global Research Perspective: Sustainovate 2025 organized by ISM Patna in July 2025