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DATA-DRIVEN ASSESSMENT OF DIDACTIC CONDITIONS IN ENGINEERING LABORATORY FORMATS: A LEARNING-ANALYTICS FRAMEWORK FOR POWER SUPPLY FUNDAMENTALS EDUCATION

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Abstract: The design of laboratory instruction in engineering education increasingly relies on structured educational data rather than intuitive judgment alone. This study proposes and applies a data-driven, expert-weighted assessment framework that converts qualitative pedagogical observations into quantifiable educational data suitable for evidence-based curriculum decisions. The framework was used to comparatively evaluate the didactic conditions of four laboratory formats employed in the Power Supply Fundamentals course at a technical university: bench-based laboratories, remotely controlled laboratories, simulator-based laboratories, and virtual reality (VR) laboratories. Eight didactic criteria — theoretical preparation, technological and material support, interactive-practical activity and real environment provision, safety and regulatory compliance, monitoring, multi-criteria assessment, reflection, and economic efficiency — were weighted by domain experts on a five-point Likert scale, and an integral educational-quality indicator was computed for each format across four practical works using a transparent, reproducible scoring procedure. The resulting dataset shows a progressive increase in integral indicator values from bench-based to remote, to simulator-based, to VR laboratories, with VR laboratories achieving the strongest overall profile, particularly for monitoring, multi-criteria assessment, and reflection, while maintaining acceptable economic-efficiency values. Beyond ranking the four formats, the study demonstrates how systematically generated educational data — rather than anecdotal impression — can directly inform laboratory-format selection in competency-oriented engineering curricula, and it proposes the resulting criterion-weighted dataset as a reusable decision-support instrument for programs considering the integration of immersive and data-instrumented technologies.

Keywords: educational data, learning analytics, didactic conditions, engineering education, virtual reality laboratories, data-driven assessment, competency-based learning

Introduction

Engineering education is undergoing a broader shift toward data-informed decision-making, in which programmatic choices about curriculum design, instructional format, and resource allocation are increasingly expected to rest on structured, quantifiable evidence rather than on tradition or intuition alone. This shift is particularly visible in discussions of educational technology, where the value of a given tool or format is judged not only by its face validity but by the extent to which it generates usable data about the learning process itself — data that can be logged, compared, aggregated, and fed back into instructional design.

The quality of engineering higher education depends significantly on the extent to which learning environments translate theoretical knowledge into demonstrable, measurable professional competence. This challenge is particularly acute in technically demanding and hazardous disciplines such as Power Supply Fundamentals, where students must acquire practical competencies related to the operation of electrical equipment, switchgear, substations, and automated metering systems, and where instructors and administrators need reliable data to judge whether a given laboratory format is actually delivering those competencies.

Laboratory instruction is a critical component of engineering education because it situates learning within authentic or near-authentic professional tasks. However, the didactic effectiveness of a laboratory format is not an inherent property of its physical form; it depends on a constellation of measurable conditions — theoretical scaffolding, realism of the task environment, availability of safety mechanisms, capacity for continuous data-based monitoring of student performance, and opportunities for reflective, evidence-grounded practice. Treating these conditions as sources of structured data, rather than as purely qualitative impressions, is what allows different laboratory formats to be compared on a common, reproducible basis.

In recent decades, the emergence of remote laboratory systems, software-based simulators, and immersive virtual reality (VR) environments has substantially expanded the range of laboratory formats available to engineering educators, and has simultaneously expanded the volume and granularity of data these environments can, in principle, generate about student interaction. Each format offers a distinct didactic profile and a distinct data profile: some formats generate rich behavioral logs, others generate almost none; some prioritize theoretical depth, others foreground safety, economic efficiency, or authentic task performance. Yet rigorous, data-grounded comparative analyses of these formats remain scarce, particularly in the domain of energy engineering education, where most existing evaluations remain descriptive rather than data-driven.

The present study addresses this gap by proposing a data-driven, expert-weighted multi-criteria framework and applying it to systematically evaluate the didactic conditions of four laboratory formats — bench-based, remotely controlled, simulator-based, and VR — as implemented in the four practical works of the Power Supply Fundamentals course. Rather than presenting a purely descriptive comparison, the study operationalizes each didactic criterion as a quantifiable data point, aggregates these points into a reproducible integral indicator, and discusses how the resulting educational dataset can directly support format-selection decisions in competency-oriented engineering programs.

Literature Review

Research on laboratory instruction in engineering education has evolved considerably over the past two decades, driven both by technological advances and by growing interest in competency-based and data-informed learning models. Traditional bench-based laboratories have long been considered the standard for practical training because of their use of authentic equipment and direct physical interaction (Feisel & Rosa, 2005). However, limitations in scalability, safety, and the availability of modern industrial apparatus — together with the near-total absence of structured performance data from bench settings — have prompted educators to explore alternative, more data-instrumented formats.

Remote laboratories, in which students control real equipment from a distance via network interfaces, have been extensively studied since the early 2000s. Researchers such as Salzmann et al. (2015) and Lowe et al. (2013) have documented their capacity to extend laboratory access beyond institutional constraints while preserving the authenticity of real-device interaction, and while producing system-level logs (timestamps, sensor readings, command histories) that bench laboratories typically do not. Nonetheless, remote formats are not universally applicable; tasks requiring hands-on assembly, physical inspection, or tactile engagement with equipment present fundamental challenges for remote delivery, and the resulting data streams say little about fine manual competency.

Simulator-based laboratories, commonly implemented through platforms such as MATLAB/Simulink, DIgSILENT PowerFactory, LabVIEW, and ETAP, offer particular advantages in theoretical modeling, safe exploration of fault and emergency conditions, and —

importantly — automatic capture of every simulated action as structured data (Hadim & Esche, 2002). Their economic efficiency is also notable, given the absence of costs associated with physical equipment procurement and maintenance. However, the fundamental limitation of simulators is their inability to replicate the physical and motor dimensions of professional practice, a deficit consistently noted in the literature on engineering skill formation (Potkonjak et al., 2016), and one that no amount of behavioral logging can fully compensate for.

VR-based laboratories have emerged as a promising alternative that bridges the gap between simulation and physical practice while substantially extending what can be captured as educational data. By providing immersive three-dimensional environments in which students interact with digital replicas of real industrial objects, VR systems can approximate the perceptual and spatial dimensions of professional work in ways that conventional simulations cannot (Radianti et al., 2020). Studies in electrical engineering education have reported significant benefits of VR for spatial understanding of circuit topology, substation layout, and relay-protection logic (Jensen & Konradsen, 2018). Because VR platforms continuously log head and hand position, gaze, task sequence, error events, and time-on-task, they enable a granularity of monitoring and multi-criteria, data-based assessment that is structurally unavailable in bench and largely unavailable in simulator formats.

Despite these advances, comparative frameworks that systematically convert didactic strengths and limitations into structured, weighted educational data remain underdeveloped; most existing comparisons are qualitative or format-specific rather than criterion-weighted and cross-format. The present study contributes to this body of knowledge by proposing an expert-weighted, criterion-based model that produces a reproducible educational dataset for the comparative assessment of laboratory didactic conditions in energy engineering education, and by explicitly treating the resulting indicators as decision-support data rather than as illustrative description.

Methodology

Classification of Laboratory Didactic Conditions

Laboratory formats in technical higher education can be classified along two dimensions: the mode of student engagement (direct versus indirect) and the degree of environmental immersion (immersive versus observational). This yields four laboratory types (Figure 1):

(1) Direct-immersive: bench-based laboratories in which students interact physically with real equipment;

(2) Direct-observational: remotely controlled laboratories in which students operate real equipment through digital interfaces without physical presence;

(3) Indirect-observational: simulator-based laboratories in which students work with mathematical and functional software models;

(4) Indirect-immersive: VR laboratories in which students engage with three-dimensional digital replicas of real equipment in an immersive environment.

Figure 1. Classification of laboratory didactic types

Didactic Assessment Criteria

Eight didactic criteria were selected to comprehensively characterize the educational quality of each laboratory format as a set of measurable data points (see Table 1). These criteria were derived from current frameworks in engineering education, competency-based learning, immersive-technology research, and laboratory pedagogy. For each criterion, a five-point Likert scale was used: 1 = very low, 2 = low, 3 = moderate, 4 = high, 5 = very high, generating an ordinal educational-data point for every criterion, laboratory work, and format combination.

Table 1
Didactic Assessment Criteria and Their Weight Coefficients

No.	Criterion	Weight Coefficient
1	Theoretical preparation level	0,10
2	Technological and material-technical support	0,15
3	Interactive-practical activity and real environment provision	0,20
4	Safety and regulatory compliance	0,10
5	Monitoring	0,10
6	Multi-criteria assessment	0,10
7	Reflection	0,10
8	Economic efficiency	0,15
	Total	**1**

The highest weight (0,20) was assigned to interactive-practical activity and real environment provision, reflecting its direct relevance to professional competency formation. Technological and material support and economic efficiency each received a weight of 0,15, given the direct relationship between equipment quality and instructional outcomes, and the practical importance of cost considerations in laboratory planning. The remaining five criteria — theoretical preparation, safety, monitoring, multi-criteria assessment, and reflection — were each assigned a weight of 0,10, reflecting their status as necessary but supporting conditions for laboratory effectiveness.

Expert weights were determined through a structured expert-elicitation procedure involving specialists in electrical power engineering, engineering-education pedagogy, and VR technology. Weight coefficients were normalized to sum to 1, so that the resulting integral indicator constitutes a single, comparable data value across all four laboratory formats.

Integral Indicator Calculation

The integral didactic quality indicator K for each laboratory was calculated according to the following formula (Equation 1):

$$K = \Sigma (w_i \cdot b_i) \quad (1)$$

where K is the integral indicator; w_i is the weight coefficient of criterion i; b_i is the score assigned to criterion i on the five-point scale. The overall format-level indicator is the mean of the integral scores across the four practical works. This procedure converts eight ordinal judgments per laboratory work into a single reproducible data value, allowing the four formats to be ranked and compared on a common numerical basis rather than through narrative description alone.

Laboratory Works Studied

Four laboratory works from the Power Supply Fundamentals course were evaluated:

Laboratory Work 1 (Lab 1): Investigation of electrical load profiles of industrial enterprises;

Laboratory Work 2 (Lab 2): Study of automatic source transfer (AST) circuits;

Laboratory Work 3 (Lab 3): Study of step-down substation circuit diagrams of industrial enterprises;

Laboratory Work 4 (Lab 4): Familiarization with automated energy metering and monitoring systems (AEMS/CAS).

Results

Bench-Based Laboratory Assessment

Bench-based laboratories constitute the current standard format for the Power Supply Fundamentals course. Prior to conducting experiments, students must study circuit diagrams, electrical apparatus, and operating principles primarily through textual instructional materials. The absence of adequate visual and interactive preparatory resources increases the time required for conceptual preparation, and — critically for a data-driven framework — this format produces almost no structured data on the preparation process itself (Figure 2).

Figure 2. Didactic conditions of bench-based laboratory instruction

Table 2 presents the criterion-level scores and integral indicators for each of the four laboratory works conducted in bench format.

Table 2

Assessment of Bench-Based Laboratory Didactic Conditions Across Eight Criteria

No.	Didactic Criterion	Lab 1	Lab 2	Lab 3	Lab 4	Mean Score
1	Theoretical preparation level	3	2	2	3	**2,5**
2	Technological and material-technical support	3	3	2	4	**3**
3	Interactive-practical activity and real environment provision	3	3	3	4	**3,25**
4	Safety and regulatory compliance	3	2	3	4	**3**
5	Monitoring	2	1	2	2	**1,75**
6	Multi-criteria assessment	2	2	1	2	**1,75**
7	Reflection	2	1	2	2	**1,75**
8	Economic efficiency	3	2	2	3	**2,5**
	Integral Indicator (K)	**2,7**	**2,15**	**2,2**	**3,15**	**2,55**

The overall integral indicator for bench-based laboratories is 2,55. Although bench laboratories provide direct hands-on experience with real equipment, their didactic conditions are constrained in several respects, and the resulting educational dataset is sparse. The safety criterion is moderately scored for most works but declines where incorrect assembly of AST circuits poses operational risk. Monitoring, multi-criteria assessment, and reflection consistently receive low scores across all four works, reflecting the practical difficulty of tracking individual student actions

in real time and of producing structured feedback data on decision-making quality in a purely physical setting.

Remotely Controlled Laboratory Assessment

Remotely controlled laboratories enable students to operate real laboratory equipment via network interfaces — PLCs, SCADA systems, data-acquisition modules, web dashboards, and IP cameras — without physical presence in the laboratory room (Figure 3). This arrangement substantially improves safety and monitoring scores, and, importantly, begins to generate system-level educational data such as timestamps, command logs, and sensor readings. Table 3 presents the assessment results.

Figure 3. Didactic conditions of remotely controlled laboratory instruction

Table 3

Assessment of Remotely Controlled Laboratory Didactic Conditions Across Eight Criteria

No.	Didactic Criterion	Lab 1	Lab 2	Lab 3	Lab 4	Mean Score
1	Theoretical preparation level	4	3	3	4	**3,5**
2	Technological and material-technical support	4	3	4	4	**3,75**
3	Interactive-practical activity and real environment provision	2	1	2	3	**2**
4	Safety and regulatory compliance	5	3	4	5	**4,25**
5	Monitoring	5	4	5	5	**4,75**
6	Multi-criteria assessment	4	2	3	4	**3,25**

No.	Didactic Criterion	Lab 1	Lab 2	Lab 3	Lab 4	Mean Score
7	Reflection	3	2	3	3	**2,75**
8	Economic efficiency	3	1	2	3	**2,25**
	Integral Indicator (K)	**3,55**	**2,2**	**3,1**	**3,75**	**3,15**

The overall integral indicator for remote laboratories is 3,15. Lab 1 (industrial load-profile investigation) and Lab 4 (AEMS familiarization) demonstrate the strongest fit for remote delivery, consistent with their emphasis on data observation and system interaction. In contrast, Lab 2 scores markedly lower in the remote format, with the interactive-practical activity criterion falling sharply, since AST circuit assembly and component-level inspection are fundamentally incompatible with remote operation and generate little usable interaction data. The substantial infrastructure investment required for PLCs, cameras, servers, and specialized software also limits the economic-efficiency scores of this format. Full migration of all four laboratory works to remote delivery is therefore not pedagogically or economically advisable on the basis of this dataset.

Simulator-Based Laboratory Assessment

Simulator-based laboratories employ dedicated engineering-software platforms — including MATLAB/Simulink, DIgSILENT PowerFactory, LabVIEW, ETAP, and PSCAD — to model electrical power systems and associated processes in a virtual environment (Figure 4). Because every simulated action can be logged automatically, this format generates a comparatively rich and low-cost stream of educational data. Table 4 summarizes the assessment findings.

Figure 4. Didactic conditions of simulator-based laboratory instruction

Table 4

Assessment of Simulator-Based Laboratory Didactic Conditions Across Eight Criteria

No.	Didactic Criterion	Lab 1	Lab 2	Lab 3	Lab 4	Mean Score
1	Theoretical preparation level	5	4	4	5	**4,5**

No.	Didactic Criterion	Lab 1	Lab 2	Lab 3	Lab 4	Mean Score
2	Technological and material-technical support	4	4	4	4	**4**
3	Interactive-practical activity and real environment provision	2	1	1	2	**1,5**
4	Safety and regulatory compliance	5	5	5	5	**5**
5	Monitoring	5	4	5	5	**4,75**
6	Multi-criteria assessment	3	2	2	3	**2,5**
7	Reflection	3	2	2	3	**2,5**
8	Economic efficiency	5	4	4	5	**4,5**
	Integral Indicator (K)	**3,85**	**3,1**	**3,2**	**3,85**	**3,5**

The overall integral indicator for simulator-based laboratories is 3,5. Simulators achieve high scores for theoretical preparation, safety, monitoring, and economic efficiency across all four laboratory works, in part because these dimensions are the easiest to capture automatically as software-generated data. Their key limitation lies in the interactive-practical activity criterion: Lab 2 and Lab 3 receive markedly low scores, reflecting the fundamental inability of software simulations to replicate the selection, physical handling, and wiring of electrical apparatus and switchgear components — a gap that no volume of logged simulation data can close. Assessment and reflection capabilities are also constrained, since all recorded student actions occur in a virtual space that does not necessarily mirror the decision-making demands of real operational environments.

VR Laboratory Assessment

VR laboratories provide students with an immersive three-dimensional environment in which they interact with high-fidelity digital replicas of electrical power systems, substations, relay-protection systems, electrical machines, and energy-infrastructure objects using VR headsets and hand controllers (Figure 5). Unlike simulators, VR environments reproduce the spatial layout and visual appearance of real industrial environments while continuously logging positional, gaze, and interaction data, enabling students to develop situational awareness and spatial-orientation skills alongside procedural competencies that are directly traceable in the resulting dataset. Table 5 presents the assessment results.

Figure 5. Didactic conditions of VR-based laboratory instruction

Table 5

Assessment of VR-Based Laboratory Didactic Conditions Across Eight Criteria

No.	Didactic Criterion	Lab 1	Lab 2	Lab 3	Lab 4	Mean Score
1	Theoretical preparation level	5	5	5	5	**5**
2	Technological and material-technical support	5	4	5	5	**4,75**
3	Interactive-practical activity and real environment provision	4	3	4	4	**3,75**
4	Safety and regulatory compliance	5	5	5	5	**5**
5	Monitoring	5	5	5	5	**5**
6	Multi-criteria assessment	5	4	5	5	**4,75**

No.	Didactic Criterion	Lab 1	Lab 2	Lab 3	Lab 4	Mean Score
7	Reflection	5	4	5	5	**4,75**
8	Economic efficiency	4	3	4	4	**3,75**
	Integral Indicator (K)	**4,65**	**3,95**	**4,65**	**4,65**	**4,48**

VR laboratories achieve the highest overall integral indicator (4,48) among all four formats, and — critically for a data-driven framework — they generate the richest and most granular educational dataset of any format examined. High scores are recorded across most criteria for all laboratory works. The interactive-practical activity criterion is comparatively strong for data-observation-oriented works but is moderated for AST-circuit assembly, reflecting the inherent limitation of VR controller-based interaction relative to the direct tactile manipulation of physical relay components and circuit wiring. Economic efficiency is scored below the maximum, acknowledging the initial investment required for VR hardware and software development, although recurring operational costs are low relative to bench-based alternatives. VR laboratories are particularly distinguished by their capacity for comprehensive, continuously logged monitoring of individual student actions and for multi-criteria, data-based assessment and reflection.

Comparative Summary

Figure 6 presents the overall integral indicators for all four laboratory formats. The progressive improvement from bench-based (2,55) to remotely controlled (3,15) to simulator-based (3,5) to VR (4,48) formats tracks closely with the volume and granularity of structured educational data that each format is able to generate about the learning process. VR laboratories demonstrate a profile of strengths that is uniquely suited to the requirements of data-informed energy-engineering education, combining near-maximal scores across safety, monitoring, assessment, and reflection criteria with a rich, continuously logged behavioral dataset, without sacrificing the interactive dimension of the learning experience.

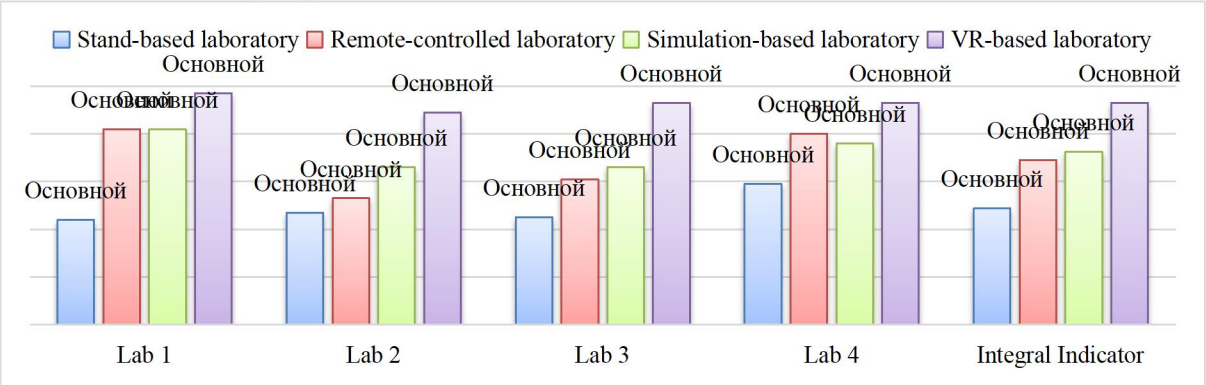


Figure 6. Overall integral didactic indicators for Power Supply Fundamentals laboratory formats

Discussion

The findings of this study offer several implications for the design and delivery of laboratory instruction in energy-engineering programs, and — more specifically — for how educational data generated within each format can be used to guide those decisions. The comparative analysis confirms that no single laboratory format is universally optimal across all four practical works, and

that format selection should be guided both by pedagogical objectives and by the kind of educational data each format is capable of producing.

Bench-based laboratories retain irreplaceable value for tasks that require direct physical engagement with equipment, particularly circuit assembly, component identification, and manual measurement procedures. The relative strength of Lab 4 in the bench format reflects the partial compatibility of AEMS familiarization with this mode of delivery, given its emphasis on operational interface rather than hazardous high-voltage tasks. Nonetheless, the systematically low scores for monitoring, reflection, and multi-criteria assessment across all bench-based works highlight a structural limitation — the near-absence of structured performance data — that cannot be easily addressed through incremental improvements to existing stand infrastructure.

Remote laboratories represent a viable alternative for laboratory works whose primary objectives center on data observation, system-level interaction, and process monitoring — objectives that are well matched to Lab 1 and Lab 4 and that naturally produce loggable data streams. The comparatively high safety and monitoring scores of this format underscore its suitability for contexts in which direct student-equipment contact carries non-trivial risk. However, the very low score for interactive-practical activity in Lab 2 illustrates the fundamental incompatibility of remote delivery with tasks requiring hands-on circuit assembly, and the corresponding data gap. The substantial infrastructure investment required also constitutes a practical barrier to institution-wide implementation of remote laboratory systems.

Simulator-based laboratories emerge as the economically efficient, data-rich format, achieving high scores for economic efficiency, safety, monitoring, and theoretical preparation. These strengths position simulators as particularly valuable for the preparatory and theoretical phases of laboratory instruction, and for tasks such as fault modeling and system analysis that do not require physical apparatus interaction and that lend themselves naturally to automatic data capture. Their consistent weakness in the interactive-practical activity criterion, however, limits their utility as a standalone replacement for bench or VR formats in laboratory works that prioritize manual skill development, regardless of how much simulation data is available.

The superior overall performance of VR laboratories across the criterion spectrum reflects the unique capacity of immersive, data-instrumented digital environments to simultaneously address multiple dimensions of didactic quality while generating a correspondingly rich educational dataset. The ability to replicate the spatial and operational context of industrial electrical infrastructure in a safe, controllable, and continuously logged environment addresses the principal limitations of each competing format. The high score for multi-criteria assessment is particularly noteworthy, as it suggests that VR systems can support the kind of granular, competency-referenced, data-based evaluation that is central to contemporary engineering-education quality frameworks.

It is important to acknowledge, however, that VR laboratories do not entirely supplant the value of physical interaction with real apparatus, nor does rich data logging substitute for tactile skill formation. The moderated score for interactive-practical activity in Lab 2 reflects the fact that VR controller-based manipulation cannot fully replicate the haptic feedback, physical resistance, and fine motor demands of actual circuit assembly. This finding suggests that a hybrid instructional model — combining VR pre-laboratory preparation and data-based formative assessment with targeted bench-based practical tasks — may represent the most pedagogically complete and best data-supported approach for complex laboratory works such as Lab 2.

The present study is subject to several limitations that warrant acknowledgment. The expert-evaluation procedure, while systematic, reflects the judgments of a specific group of specialists and may not generalize across all institutional contexts or national curriculum frameworks. The four

laboratory works analyzed are specific to the Power Supply Fundamentals course at one technical university, and the transferability of the resulting dataset and findings to other energy-engineering courses requires further investigation. Additionally, the present study relies on expert-assigned criterion scores rather than on directly logged behavioral data from each platform; an important next step is to validate and, where possible, replace these expert judgments with automatically captured interaction data (time-on-task, error rates, action sequences) from each laboratory format. Future research should examine the relationship between laboratory format, structured educational data, and measurable competency outcomes in longitudinal, data-driven designs.

Conclusion

This study has proposed and applied a data-driven, expert-weighted framework for evaluating the didactic conditions of four laboratory formats — bench-based, remotely controlled, simulator-based, and virtual reality — as implemented in the Power Supply Fundamentals course in an energy-engineering program. Using an eight-criterion expert-weighted framework, integral didactic-quality indicators were calculated for each format across four laboratory works, producing a structured, reproducible educational dataset rather than a purely descriptive comparison.

The results demonstrate a clear differentiation between formats, with integral indicators rising from bench-based (K = 2,55), to remote (K = 3,15), to simulator-based (K = 3,5), to VR laboratories (K = 4,48). VR laboratories exhibited the strongest overall didactic profile and the richest associated educational dataset, achieving near-maximum scores across safety, theoretical preparation, monitoring, multi-criteria assessment, and reflection criteria. Their sole relative weaknesses — interactive-practical activity for hands-on circuit-assembly tasks and initial economic investment — suggest that VR-enhanced instruction is most effective, and best supported by data, when integrated into hybrid pedagogical models rather than implemented as a wholesale replacement of all existing laboratory formats.

These findings contribute a reproducible, data-driven framework for laboratory-format selection in competency-oriented engineering curricula, and offer the resulting criterion-weighted dataset as a decision-support instrument for institutions considering investment in VR laboratory infrastructure. The study underscores the value of treating laboratory didactic conditions as a multi-dimensional, data-generating construct rather than a matter of qualitative impression, and calls for continued empirical, data-driven research into the relationship between immersive, instrumented laboratory environments and measurable professional-competency outcomes.

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