# A Quasi-Experimental Evaluation of An Integrated Digital Learning System for Automotive Electrical Systems Education

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***Abstract***
*The accelerating digitalisation and electrification of the automotive industry has widened the gap between conventional lecture-based instruction and the diagnostic, analytical, and information-technology competencies required of automotive engineering graduates. This study evaluates the pedagogical effectiveness of an integrated digital learning system developed for the course Automotive Electrical Systems within undergraduate Transport Engineering programmes. A quasi-experimental, non-equivalent control-group design was implemented across three technical higher education institutions over a three-year period, involving 416 undergraduate students (experimental group, n = 209; control group, n = 207). The experimental group received a digital learning system combining virtual laboratories, a learning-management platform, protocol-level network simulation, electronic-control-unit practicum tasks, project-based learning, and electronic assessment, while the control group received conventional instruction covering identical curricular content. Competency was measured across five domains using a criterion-referenced rubric, and group differences were evaluated using an independent-samples t-test and Pearson's chi-square test at a 95% confidence level. No significant baseline difference existed between groups ($p > 0.05$); following the intervention, the experimental group achieved significantly higher composite competency scores ($t = 4.94$, $p < 0.05$; $\chi^2 = 25.30$, $p < 0.05$), with an instructional-effectiveness coefficient of 1.134 and the largest gain observed in diagnostic competencies (+31.6 versus +6.3 percentage points). The results demonstrate that a systematically integrated digital learning system produces statistically and practically significant improvements in applied engineering competencies relative to conventional instruction, offering a validated, reproducible architecture for technology-enhanced engineering curricula in resource-constrained institutional contexts.*

***Keywords—*** *digital learning systems; virtual laboratories; quasi-experimental evaluation; engineering education technology; educational data analytics*

# I. Introduction

## *A. Background*

The global automotive industry has undergone a profound structural transformation driven by the convergence of embedded electronics, high-speed in-vehicle communication networks, and software-defined architectures. Contemporary vehicles function as complex cyber-physical systems composed of numerous electronic control units (ECUs), dense sensor networks, and safety-critical embedded software [1]. The accelerating adoption of electric and hybrid-electric powertrains has further intensified the technical demands placed on automotive engineering graduates, who must demonstrate competence in high-voltage electrical architectures, battery management systems, and vehicle communication protocols in addition to conventional circuit theory [2], [3].

## *B. Motivation*

International engineering-education research has converged on a set of pedagogical responses to this technological shift, including competency-based education, project-based learning, and simulation- or laboratory-based instruction, that reposition the learner as an active participant in authentic, industry-relevant tasks [4]–[6]. Digital learning technologies provide the infrastructural basis for this shift: virtual and remote laboratories allow diagnostic and troubleshooting exercises to be conducted without the capital cost, safety risk, or scheduling constraints of physical test benches, and meta-analytic evidence indicates that virtual-laboratory instruction produces learning gains comparable to, and in resource-constrained contexts exceeding, physical laboratory instruction [7], [8]. Learning-management platforms and digital resources extend instruction beyond the scheduled classroom and enable continuous, data-informed monitoring of student progress [9]. International and national policy frameworks reinforce this direction: global monitoring bodies call for purposeful, equity-conscious digital-technology adoption in education [10], [11], the development of teachers' and learners' information and communication technology (ICT) competencies is formally codified as a policy priority [12], and cross-national indicators document the accelerating institutionalisation of digital assessment and learning infrastructure across higher-education systems [13].

## *C. Problem Statement*

Despite this favourable technological and policy environment, instruction in automotive electrical systems courses at many technical universities continues to be dominated by lecture-based delivery, with limited access to contemporary diagnostic equipment and to digital learning resources capable of supporting independent, self-paced study. Lecture-centred instructional models, while efficient for transmitting declarative knowledge, are structurally limited in their capacity to cultivate the diagnostic reasoning, procedural fluency, and authentic problem-solving skills that automotive electronic systems now require [4]. This mismatch between instructional practice and industrial competency requirements motivates the central problem addressed in this study: conventional instruction alone is insufficient to develop the applied diagnostic and analytical competencies demanded of automotive engineering graduates, and the effectiveness of digitally integrated alternatives has not been rigorously quantified for this specific technical domain.

### *D. Research Gap*

A substantial body of research has examined individual digital-pedagogical interventions in isolation, including virtual laboratories [14], simulation-based science, technology, engineering, and mathematics (STEM) instruction [15], project-based learning [16], and flipped or blended delivery models [17], [18], generally reporting favourable effects on achievement and engagement. Automotive-specific digital instruction research has similarly tended to examine isolated tools, such as virtual-reality laboratories for automotive systems [19] or virtual practicum platforms for electrical components [20], [21], rather than a comprehensively integrated digital learning system evaluated through a controlled, statistically powered, multi-institutional design. Consequently, empirical evidence quantifying the combined effect of an integrated, multi-component digital learning system, rather than a single tool, on automotive electrical systems competency remains scarce, and this gap is particularly pronounced within Central Asian technical higher-education systems, which are underrepresented in the internationally indexed engineering-education literature.

### *E. Research Objectives*

This study pursues three objectives: (i) to design and implement an integrated digital learning system for the Automotive Electrical Systems course, combining virtual laboratories, network-protocol simulation, electronic-control-unit practicum tasks, project-based learning, and electronic assessment within a single pedagogical architecture; (ii) to evaluate the effect of this system on students' theoretical knowledge, circuit-analysis competence, diagnostic skill, problem-solving ability, and professional communication competence relative to conventional instruction; and (iii) to determine the statistical significance and practical magnitude of any observed differences using inferential procedures appropriate to a quasi-experimental design.

### *F. Contributions*

- A validated, reproducible architecture for an integrated digital learning system combining virtual laboratories, protocol-level simulation, electronic-control-unit practicum tasks, project-based learning, and electronic assessment for automotive electrical systems education.
- Multi-institutional, statistically powered empirical evidence (N = 416, three institutions, three years) quantifying the effect of the integrated system relative to conventional instruction, extending an evidence base disproportionately concentrated in Western and East Asian contexts.
- A five-domain, criterion-referenced competency-assessment architecture, together with a formalised group-allocation and intervention procedure, that is directly reproducible for related automotive and electromechanical engineering courses.

### *G. Paper Organization*

The remainder of this paper is organized as follows. Section II critically reviews related work on digital learning technologies in engineering education and situates the present study within the identified research gap. Section III describes the research design, the architecture of the digital learning system, the experimental procedure, and the evaluation methodology, including the mathematical formulation of the statistical tests employed. Section IV reports the experimental results. Section V discusses the significance, implications, and limitations of the findings in relation to prior work. Section VI concludes the paper and outlines directions for future research.

## II. Related Work

### *A. Digital Transformation in Engineering Education*

Digital transformation (DT) in higher education is increasingly conceptualised as a systemic reconfiguration of curricula, pedagogy, assessment, and infrastructure rather than the incidental adoption of individual tools [22]. Systematic reviews of DT in engineering faculties report that digitally mature institutions restructure content, delivery, and assessment simultaneously [23], and that the benefits of DT are frequently offset by inadequate staff digital competence and inconsistent institutional strategy [24], [25]. Evidence from the African higher-education context similarly indicates a transition from predominantly lecture-based instruction toward active, technology-enhanced, blended, problem-based, and competency-oriented pedagogies, although infrastructure, faculty capacity, and access to digital technologies remain significant implementation constraints [47]. A tripartite logical framework—value logic, technological logic, and practical logic—has been proposed for understanding how DT initiatives translate into measurable pedagogical outcomes [26], directly informing the systems-level design rationale adopted in Section III of this study.

### *B. Virtual Laboratories and Simulation-Based Learning*

Virtual and remote laboratories are among the most extensively validated digital interventions in engineering education. A meta-analysis of 46 empirical studies reported consistently positive effects of virtual-laboratory use on motivation, conceptual understanding, and skill acquisition, with effect sizes comparable to physical laboratory instruction [7]. A systematic review of implementations between 2018 and 2023 reported consistent gains in cost-effectiveness and safety while cautioning that pedagogical integration quality, rather than the technology itself, determines learning impact [8]. A structural typology distinguishing fully virtual, hybrid, and augmented laboratory configurations [14] directly informed the laboratory-component design used in this study, and evidence from simulation-based STEM instruction confirms that digital simulations improve conceptual transfer when embedded within a structured pedagogical sequence rather than deployed as standalone activities [15].

### *C. Automotive-Specific Digital Instruction*

Within the automotive-education literature, prior work has applied virtual and simulation-based instruction to electrical practicum courses, high-voltage electric-vehicle components, and diagnostic training. A virtual laboratory developed specifically for an automotive electrical practicum course reported improved comprehension of circuit-level fault diagnosis [20]; a virtual teaching system for high-voltage electric-vehicle components directly addressed the electrification-driven curricular gap identified in Section I [21]; and a virtual-reality automotive systems laboratory built on consumer VR hardware reported strong learner acceptance under remote-instruction conditions [19]. Curricular surveys in Nigeria [3] and Jordan [2] both identify insufficient access to modern diagnostic equipment as the principal barrier to preparing automotive graduates, while a broader analysis argues that the translation of electric-vehicle research into formal curricula lags behind industrial adoption [1]. Each of these studies, however, evaluates a single tool or platform rather than a multi-component, statistically evaluated instructional system.

### *D. Project-Based and Competency-Based Learning*

Project-Based Learning (PBL) has accumulated substantial meta-analytic support for developing technical and professional competencies in engineering students. A meta-analysis of 66 experimental and quasi-experimental studies confirmed moderate-to-large positive effects of PBL relative to conventional instruction [16], corroborated by a twenty-one-year, engineering-specific meta-analysis [6] and by evidence of PBL's particular strength in developing non-technical competencies alongside technical mastery [5]. Competency-based education (CBE) has been advanced as the most appropriate overarching framework for restructuring engineering curricula toward professionally aligned outcomes [4]. A quasi-experimental study combining CBE with digital and simulation-based resources in a technical health-sciences programme, using a sequential-cohort design methodologically analogous to the present study, reported significant post-intervention gains [27], supporting the combined CBE-digital-system approach adopted here.

### *E. Learning Platforms, Digital Assessment, and Learning Analytics*

Learning-management platforms enhance learner engagement primarily through features supporting continuous feedback and resource accessibility rather than through content delivery alone [9]. Instrument-development research on digital-assessment adoption indicates that successful implementation depends on aligning assessment format with the targeted competency domain rather than merely digitising paper instruments [28]. Learning analytics is increasingly positioned as the connective infrastructure enabling continuous, data-informed feedback loops between instructional design and student performance [29], a principle reflected in the centralised electronic monitoring architecture described in Section III.

### *F. Blended Learning and Emerging Technologies*

Blended and flipped delivery models, which combine digital pre-instruction with in-person application, have demonstrated strong effects in electrical and electronics engineering contexts, with a multi-cohort quasi-experimental evaluation in an upper-division electrical engineering course reporting sustained performance gains [17] and a bibliometric mapping documenting a maturing evidence base since 2015 [18]. More recent work has begun to examine artificial-intelligence-driven intelligent tutoring systems for personalised feedback [30] and controlled comparisons of virtual-reality and digital-twin laboratory instruction reporting outcomes statistically comparable to physical laboratories [31]; these technologies are addressed as future extensions of the present system in Section VI.

### *G. Methodological Foundations*

Quasi-experimental designs remain the dominant approach for evaluating pedagogical interventions in authentic educational settings where individual-level randomisation is administratively infeasible [32], and the internal validity of non-equivalent control-group designs depends critically on demonstrable baseline equivalence between groups [33], a condition directly addressed in Section IV-A of this study. Mixed-methods approaches are increasingly recognised as methodologically appropriate for large-scale educational evaluation [34], with systematic evidence indicating that the prevalence and quality of mixed-methods designs in education research has risen substantially over the past decade [35]. Correct application of internal-consistency reliability statistics, particularly Cronbach's alpha, remains a persistent methodological concern; recent reviews document both the continuing overuse of alpha as a

default index and the availability of more appropriate alternatives depending on instrument structure [36], [37].

### *H. Comparative Summary and Research Gap*

Table I summarises representative studies discussed above alongside the present study, highlighting differences in intervention scope, evaluation design, and domain specificity. As the comparison indicates, existing studies predominantly evaluate a single digital tool (e.g., a virtual laboratory or a flipped-classroom format) within general engineering or unrelated technical domains, using single-institution samples. The present study is distinguished by its evaluation of an integrated, multi-component digital learning system—rather than an isolated tool—applied specifically to automotive electrical systems education and evaluated across three institutions with a statistically powered sample. This combination of integration, domain specificity, and multi-institutional statistical power addresses the research gap identified in Section I-D.

***Table I. Comparison Of Representative Related Studies***

| Study | Domain | Intervention Scope | Design | Sample |
|---|---|---|---|---|
| Li & Liang [7] | General engineering | Virtual laboratories (meta-analysis) | Meta-analysis, 46 studies | Multiple studies |
| Irawan et al. [20] | Automotive electrical | Single virtual laboratory | Development + evaluation | Single institution |
| Wu et al. [21] | EV high-voltage components | Single virtual teaching system | System development | Single institution |
| Zhang & Ma [16] | General engineering | Project-based learning (meta-analysis) | Meta-analysis, 66 studies | Multiple studies |
| Kattel et al. [17] | Electrical engineering | Flipped classroom (single format) | Quasi-experimental, multi-cohort | Single institution |
| Qi & Zhou [27] | Medical imaging technology | CBE + digital/simulation resources | Quasi-experimental, sequential cohort | Single institution, n=120 |
| Present study | Automotive electrical systems | Integrated system: virtual labs, LMS, protocol simulation, ECU tasks, PBL, e-assessment | Quasi-experimental, non-equivalent control group | Three institutions, N=416 |

## III. Methodology

This section describes the research design, the architecture of the digital learning system, the experimental procedure, the instrumentation, and the evaluation methodology, including the mathematical formulation of the statistical tests employed, so that the study is fully reproducible.

### *A. Research Design*

A quasi-experimental, non-equivalent control-group design with pre-test and post-test measurement was adopted. Individual-level randomisation was administratively infeasible within intact university course sections; this constraint is characteristic of, and methodologically accepted within, applied educational-intervention research conducted in authentic classroom settings [32], [33]. The design comprised two intact groups—an experimental group receiving the integrated digital learning system and a control group receiving conventional instruction—both assessed with an identical diagnostic instrument before the intervention and an identical competency instrument after one academic semester.

Threats to internal validity were addressed as follows. Selection bias was mitigated by allocating groups on documented prior grade point average and baseline diagnostic score, with equivalence verified statistically before the intervention (Section IV-A) [33]. History and maturation threats were controlled by running both groups concurrently within the same institution and semester. Instrumentation threats were controlled by administering identical instruments, scored against the same rubric, to both groups. Diffusion of treatment was mitigated by assigning groups at the level of intact course sections taught in separate timetable slots.

### *B. Study Setting and Participants*

The study was conducted at three public technical higher education institutions in Uzbekistan, denoted Institution A, Institution B, and Institution C to preserve double-blind review. Each institution maintains an accredited Transport Engineering programme with an established Automotive Electrical Systems course, automotive laboratory infrastructure, and internet-connected computing facilities. The institutional setting operates within a national programme of higher-education digitalisation that mandates the integration of information and communication technologies into curricula [43], [44]. The analytic sample comprised 416 undergraduate students, with near-equal allocation to the experimental (n = 209, 50.2%) and control (n = 207, 49.8%) conditions, as summarised in Table II. Inclusion required active enrolment in the course and completion of both diagnostic and summative assessments; exclusion criteria removed students with incomplete records or prior course failure. Gender and precise age were not captured in the source institutional records and are not reported; this is addressed as a limitation in Section V-D.

*TABLE II. PARTICIPANT DISTRIBUTION BY INSTITUTION AND GROUP*

| Institution | Experimental Group | Control Group | Total |
|---|---|---|---|
| Institution A | 65 | 65 | 130 |
| Institution B | 65 | 63 | 128 |
| Institution C | 79 | 79 | 158 |
| Total | 209 | 207 | 416 |

### *C. Digital Learning System Architecture*

The experimental group received an integrated digital learning system comprising ten interoperating instructional components, summarised in Table III and illustrated conceptually in Fig. 1. The design rationale for combining these components, rather than deploying a single tool in isolation, follows directly from the digital-transformation literature reviewed in Section II-A, which indicates that isolated tool adoption yields more limited pedagogical impact than systemic redesign of content, delivery, and assessment [22], [26]. The components were integrated through a first-principles instructional sequence—activation of prior knowledge, demonstration, guided application, and independent task performance [38]—and aligned with constructive-alignment principles linking intended learning outcomes, learning activities, and assessment tasks [39]. Multimedia components (interactive presentations, instructional video) were designed in accordance with established cognitive-load and multimedia-learning principles to minimise extraneous processing demands [41].



*Fig. 1. System architecture of the integrated digital learning system, showing the mapping from instructional components to mediating pedagogical processes and measured competency outcomes.*

*TABLE III. DIGITAL LEARNING SYSTEM COMPONENTS*

| Component | Pedagogical Function |
|---|---|
| Virtual laboratory module | Risk-free, repeatable circuit construction and fault-diagnosis practice |
| Electronic assessment engine | Immediate, criterion-referenced feedback |
| QR-linked resource repository | Extended access to digital learning materials |
| Interactive multimedia content | Annotated diagrams, animation, video-based instruction |
| Diagnostic simulator | Industry-representative fault-finding and scan-tool practice |

| Component | Pedagogical Function |
|---|---|
| CAN/LIN protocol simulator | In-vehicle network communication training |
| ECU practicum module | Parameter reading, fault-code interpretation, reprogramming |
| Project-based learning tasks | Team-based multi-fault diagnostic scenarios |
| Collaborative workspace | Structured small-group problem-solving |
| Video/manual repository | Self-paced review and remediation |

The control group followed the officially approved curriculum through conventional lecture-based instruction, physical-equipment laboratory sessions, and paper-based assessment, covering identical topical content and learning outcomes, so that observed differences were attributable to instructional methodology rather than curricular content.

### *D. Experimental Procedure*

The experiment was implemented in three sequential stages—diagnostic, formative, and summative—illustrated in Fig. 2. During the diagnostic stage, baseline knowledge and practical competence were assessed for both groups. During the formative stage, spanning one full academic semester, the experimental group received the digital learning system described in Section III-C while the control group continued under conventional instruction; both groups were monitored continuously. During the summative stage, both groups completed an identical post-intervention competency assessment. The procedure is formalised in Algorithm 1.

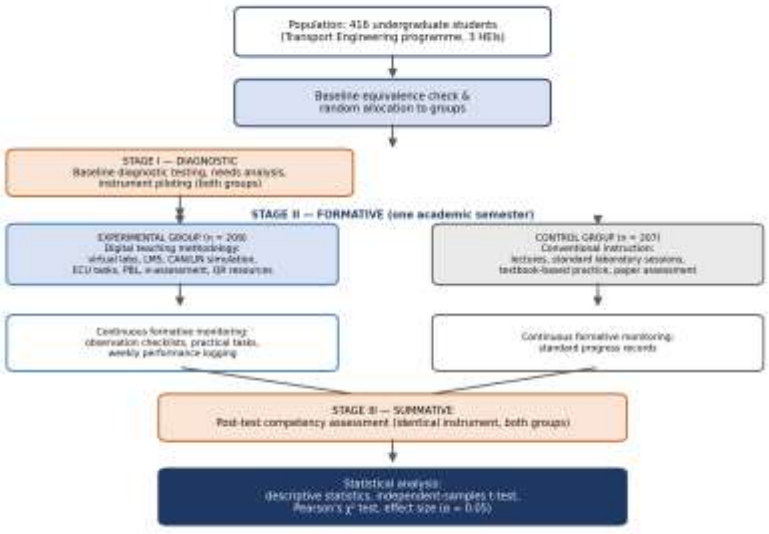



*Fig. 2. Three-stage experimental workflow.*

**Algorithm 1: Group Allocation and Intervention Procedure**

```
Input: Student roster S for each institution I in {A,B,C};
       prior GPA g(s), baseline diagnostic score d(s) for s in S
Output: Group label L(s) in {EG, CG} for each s in S;
       post-intervention competency score C(s)

1: for each institution I do
2:   Rank students s in S_I by (g(s), d(s))
3:   Partition S_I into matched pairs P_k = (s_i, s_j)
4:   for each pair P_k do
5:     Assign one student to EG, the other to CG
6:     (assignment balanced across pairs; timetable-separated)
7:   end for
8: end for
9: Verify baseline equivalence: t-test on d(s) for EG vs CG
10: if p <= 0.05 then re-balance allocation and repeat step 9
11: for each academic semester do
12:   for s in EG: deliver digital learning system (Sec. III-C)
13:   for s in CG: deliver conventional instruction
14:   log formative indicators for all s in centralised database
15: end for
16: Administer identical post-intervention assessment to all s
17: Compute C(s) using rubric (Table V); return {L(s), C(s)}
```

### *E. Sampling Procedure*

A purposive institutional sampling strategy selected the three participating institutions based on the infrastructural and curricular equivalence criteria described in Section III-B. Within each institution, intact course sections were assigned to condition using the matched quasi-random allocation procedure formalised in Algorithm 1, illustrated in Fig. 3. No formal a priori power

analysis was conducted; however, the achieved sample (N = 416) substantially exceeds conventional minimum-sample thresholds for detecting medium effect sizes in independent-samples comparisons at $\alpha = 0.05$ with power of 0.80.

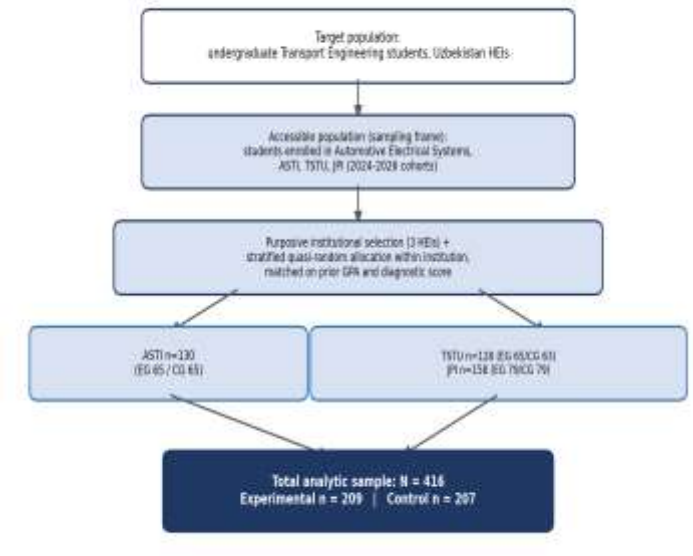



*Fig. 3. Sampling and group-allocation procedure.*

### *F. Research Instruments*

Six instrument categories were employed, summarised in Table IV: a diagnostic test (baseline theoretical knowledge and elementary circuit-analysis skill); a post-intervention competency assessment structurally parallel to the diagnostic instrument; a student questionnaire capturing engagement and perceived usefulness; an instructor-completed observation checklist; a criterion-referenced performance rubric (Table V); and a practical examination assessed against the same rubric. Instrument development proceeded through curriculum mapping, expert review by senior automotive-engineering faculty, and pilot administration outside the main sample.

*TABLE IV. RESEARCH INSTRUMENTS*

| Instrument | Purpose | Administration Point |
|---|---|---|
| Diagnostic test | Baseline knowledge and circuit-analysis skill | Pre-intervention |
| Student questionnaire | Engagement and perceived usefulness | Formative stage |
| Observation checklist | Practical engagement and procedure adherence | Throughout formative stage |

| Instrument | Purpose | Administration Point |
|---|---|---|
| Performance rubric | Criterion-referenced scoring (Table V) | Both stages |
| Competency assessment | Post-intervention knowledge and applied skill | Post-intervention |
| Practical examination | Observed diagnostic task performance | Post-intervention |

### *G. Evaluation Metrics*

Competency was operationalised as a composite score across five domains—theoretical knowledge, electrical circuit analysis, diagnostic competencies, practical laboratory performance, and independent project work—each scored 0–20 for a maximum composite of 100 (Table V). The domain structure spans the knowledge, application, and analysis levels of Bloom's taxonomy of cognitive objectives [40], providing construct validity for the rubric. Variables are defined in Table VI: the independent variable was instructional condition (digital system vs. conventional); dependent variables were the five domain scores and the composite performance-level classification; control variables (curricular content, learning outcomes, contact hours) were held constant across groups; and institution and prior academic performance were used as blocking variables for allocation.

*TABLE V. COMPETENCY ASSESSMENT RUBRIC*

| Criterion | Max. Score |
|---|---|
| Theoretical knowledge | 20 |
| Electrical circuit analysis | 20 |
| Diagnostic competencies | 20 |
| Practical laboratory performance | 20 |
| Independent project work | 20 |
| Total | 100 |

*TABLE VI. VARIABLE DEFINITIONS*

| Type | Variable(s) |
|---|---|
| Independent | Instructional condition (digital system vs. conventional) |
| Dependent | Five domain scores; composite performance-level classification |
| Control | Curricular content; learning outcomes; contact hours |
| Blocking | Institution; prior GPA; baseline diagnostic score |

### *H. Mathematical Formulation*

Baseline equivalence and post-intervention differences between groups were tested using an independent-samples t-test. For experimental group mean $\bar{X}_1$ ($n_1 = 209$) and control group mean $\bar{X}_2$ ($n_2 = 207$), with sample standard deviations $s_1$ and $s_2$, the test statistic is:

$$t = (\bar{X}_1 - \bar{X}_2) / \sqrt{( s_1^2/n_1 + s_2^2/n_2 )} \quad (1)$$

The association between instructional condition and the four-level ordinal performance classification (excellent, good, satisfactory, unsatisfactory) was tested using Pearson's chi-square statistic, where $O_i$ and $E_i$ denote the observed and expected frequencies of cell i:

$$\chi^2 = \Sigma_i (O_i - E_i)^2 / E_i \quad (2)$$

Practical significance was expressed through an instructional-effectiveness coefficient (IEC), defined as the ratio of the experimental group's post-intervention mean composite score (M_EG) to that of the control group (M_CG):

$$IEC = M_EG / M_CG \quad (3)$$

Statistical significance for (1) and (2) was set at $\alpha = 0.05$ (95% confidence level) throughout.

### *I. Implementation Environment*

The digital learning system was delivered using each institution's existing internet-connected computer laboratories and a web-accessible learning-management platform. Statistical computation for (1)–(3) was performed in Microsoft Excel, consistent with the scale and tabular structure of the dataset. [Author to Provide: specific virtual-laboratory software, simulator product name/version, and LMS platform name, if disclosure does not compromise double-blind review.]

### *J. Reliability and Validity*

Internal consistency of the multi-item instruments was evaluated using Cronbach's alpha, applying interpretive thresholds and cautions established in recent methodological reviews of alpha's appropriate use in educational measurement [36], [37]; reliability was assessed per competency subscale rather than for the instrument as an undifferentiated whole. [Author to Provide: pilot-stage Cronbach's alpha coefficients per subscale.] Inter-rater reliability for the observation checklist and practical-examination scoring was addressed through joint rater training and calibration on a common sample of performances prior to the formative stage. Content validity was established through curriculum mapping and expert-panel review; face validity was assessed

through pilot-administration feedback; and construct validity was supported by the theoretically grounded five-domain rubric structure aligned with Bloom's taxonomy [40].

### *K. Ethical Considerations*

The study was conducted with the formal permission of the academic administration of each participating institution. All participants were informed of the study's purpose, procedures, and voluntary nature prior to data collection; participation entailed no assessment or curricular disadvantage for students who preferred not to have their anonymised data included. Data were de-identified using participant-level codes, stored on access-restricted institutional systems, and analysed only in aggregate form. Both groups received complete, curriculum-aligned instruction and assessment, differing only in instructional methodology, consistent with the principle of educational equipoise.

## IV. Results

### *A. Baseline Equivalence*

Prior to the intervention, both groups completed an identical diagnostic assessment (Table VII). 9.6% of experimental-group students achieved an excellent rating compared with 6.8% of control-group students, while unsatisfactory performance was recorded for 33.0% and 35.3%, respectively. Applying (1) to the pre-intervention composite scores yielded no significant difference ($p > 0.05$), confirming baseline equivalence and satisfying the internal-validity precondition specified in Section III-A.

*TABLE VII. INITIAL (PRE-INTERVENTION) RESULTS*

| Group | Excellent | Good | Satisf. | Unsatisf. |
|---|---|---|---|---|
| Experimental (n=209) | 20 | 31 | 89 | 69 |
| Control (n=207) | 14 | 34 | 86 | 73 |

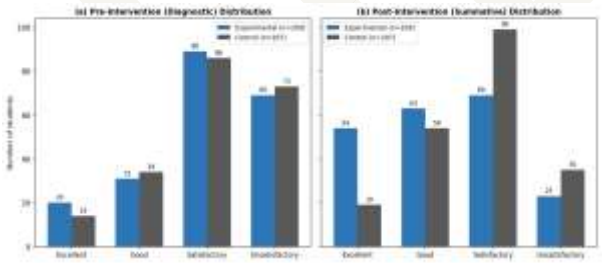


*Fig. 4. Performance-level distribution before and after the intervention.*

### *B. Post-Intervention Performance*

Following one academic semester, both groups were reassessed using identical criteria (Table VIII, Fig. 4). Experimental-group students achieving an excellent rating increased from 20 to 54, while unsatisfactory performance decreased from 69 to 23. The control group showed comparatively modest movement (excellent: 14→19; unsatisfactory: 73→35), indicating that conventional

instruction produced measurably smaller gains than the digital learning system over an equivalent instructional period.

*TABLE VIII. FINAL (POST-INTERVENTION) RESULTS*

| Group | Excellent | Good | Satisf. | Unsatisf. |
|---|---|---|---|---|
| Experimental (n=209) | 54 | 63 | 69 | 23 |
| Control (n=207) | 19 | 54 | 99 | 35 |

### *C. Competency-Domain Analysis*

Gains were computed separately for the five competency domains defined in Table VI (Table IX, Fig. 5). The digital learning system produced positive gains across all domains, substantially exceeding the corresponding control-group gains. The largest differential was observed in diagnostic competencies (+31.6 vs. +6.3 percentage points), followed by electrical circuit analysis (+27.8 vs. +5.2) and engineering problem-solving (+25.2 vs. +4.8). This pattern indicates that the system was particularly effective at developing applied, diagnostic, and analytical competencies rather than producing uniform gains across all domains.

*TABLE IX. COMPETENCY GAINS BY GROUP (PERCENTAGE POINTS)*

| Competency | Exp. Group | Ctrl. Group |
|---|---|---|
| Theoretical knowledge | +23.4 | +4.6 |
| Circuit analysis | +27.8 | +5.2 |
| Diagnostic skills | +31.6 | +6.3 |
| Problem-solving | +25.2 | +4.8 |
| Communication | +21.9 | +3.9 |

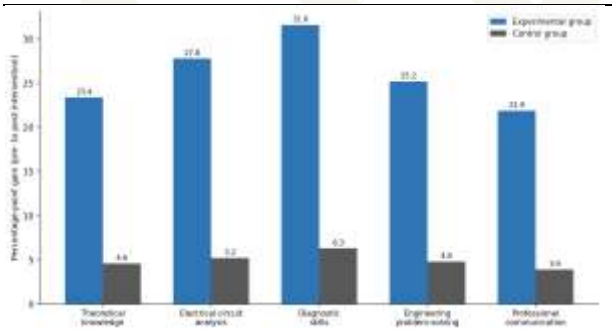


*Fig. 5. Gains in professional competencies by group.*

### *D. Inferential Statistical Analysis*

Applying (1) to post-intervention composite scores yielded $t = 4.94$, exceeding the critical value at the 95% confidence level ($p < 0.05$); the experimental-group mean ($M = 3.71$) significantly exceeded the control-group mean ($M = 3.27$). Applying (2) to the performance-level classification

yielded $\chi^2 = 25.30$, exceeding its critical value and leading to rejection of the null hypothesis specified in Section I-E. The convergence of parametric and non-parametric results (Table X) substantially strengthens confidence in the robustness of the inferential conclusion.

*TABLE X. STATISTICAL ANALYSIS SUMMARY*

| Indicator | Value |
|---|---|
| Mean, experimental group | 3.71 |
| Mean, control group | 3.27 |
| IEC, Eq. (3) | 1.134 |
| t-value, Eq. (1) | 4.94 |
| $\chi^2$ value, Eq. (2) | 25.30 |
| Confidence level | 95% ($\alpha$=0.05) |

Applying (3), IEC = 1.134, indicating that experimental-group performance exceeded control-group performance by 13.4%. This composite improvement was concentrated in applied, diagnostic, and problem-solving domains rather than distributed uniformly, directly addressing the research objective specified in Section I-E(ii).

## V. Discussion

### *A. Significance of Findings*

The results demonstrate that systematic integration of a digital learning system into Automotive Electrical Systems instruction produces statistically significant improvements in learning outcomes ($t = 4.94$, $\chi^2 = 25.30$, both $p < 0.05$), with a 13.4% instructional-effectiveness gain concentrated in applied and diagnostic competency domains. The magnitude and direction of this effect is consistent with meta-analytic evidence on virtual laboratories [7], project-based learning [16], and flipped or blended engineering instruction [17], strengthening confidence that the observed effect reflects a genuine pedagogical mechanism rather than a context-specific artefact.

### *B. Comparison with Prior Work*

As summarised in Table I, prior automotive-specific studies evaluate single tools within single institutions [20], [21], [19], whereas the present study evaluates an integrated multi-component system across three institutions with a statistically powered sample. The finding that diagnostic competencies exhibited the largest experimental-control differential is theoretically consistent with cognitive-load and multimedia-learning principles [41]: virtual laboratories and diagnostic simulators reduce the extraneous cognitive burden associated with physical equipment setup, freeing cognitive resources for the germane processing of fault-diagnosis logic. This interpretation is consistent with the argument that virtual-laboratory design quality, not merely digital format, determines learning impact [14], and with evidence that authentic, industry-representative simulation tasks strengthen transfer of diagnostic reasoning [15]. The comparatively smaller, though still significant, gain in theoretical knowledge (+23.4 vs. +4.6 points) indicates that the system's advantage was concentrated at the application and analysis levels of Bloom's taxonomy [40] rather than at the declarative-knowledge level, consistent with the theoretical positioning of project-based and simulation-based learning [4], [5].

### *C. Practical Implications*

From a systems perspective, the findings support the proposition that learning in technologically mediated environments is distributed across networked resources—the learning-management platform, virtual laboratories, peer collaboration, and instructor feedback jointly constituting the learning environment—rather than residing solely in direct instructor-to-student transmission [42]. Practically, the results suggest that technical universities operating under infrastructural constraints similar to those described in Section III-B can achieve meaningful competency gains without full physical-laboratory modernisation, provided that virtual and simulation-based alternatives are pedagogically well-integrated rather than deployed as a supplementary add-on. This has direct relevance for resource-constrained technical higher-education systems beyond the present study context, including those reporting comparable infrastructural barriers to automotive-technology education [3], [2].

### *D. Limitations*

Several limitations should be acknowledged. First, the non-equivalent control-group design means that, despite matched allocation and verified baseline equivalence, unmeasured confounding at the section or instructor level cannot be entirely excluded. Second, the sample was drawn exclusively from Uzbekistani technical universities; generalisation to other national systems or curricular traditions should be made cautiously. Third, the source dataset did not capture gender or precise age, precluding demographic subgroup analysis. Fourth, all inferential analysis used a t-test and chi-square test appropriate to the dataset structure; more advanced procedures—analysis of covariance controlling for baseline score, multilevel modelling accounting for institutional clustering, or standardised effect-size statistics—would strengthen future replications. Fifth, self-reported engagement data are subject to novelty-effect bias inherent to technologically novel interventions, which a single-semester design cannot fully disentangle from sustained pedagogical benefit.

## VI. Conclusion

This study designed, implemented, and empirically evaluated an integrated digital learning system for the Automotive Electrical Systems course through a three-year, multi-institutional quasi-experimental investigation involving 416 undergraduate students. The system combined virtual laboratories, a learning-management platform, protocol-level network simulation, electronic-control-unit practicum tasks, project-based learning, and electronic assessment, contrasted against conventional instruction covering identical curricular content.

The results provide statistically robust evidence, converging across parametric and non-parametric tests ($t = 4.94$; $\chi^2 = 25.30$; both $p < 0.05$), that the integrated system produced significantly greater competency gains than conventional instruction, with an overall instructional-effectiveness advantage of 13.4% and particularly pronounced gains in applied diagnostic reasoning. The principal contributions of this work are: a reproducible digital-learning-system architecture and formalised allocation procedure (Algorithm 1); multi-institutional statistical evidence of its effectiveness; and a validated five-domain competency-assessment instrument applicable to related automotive and electromechanical engineering courses.

The principal limitations, detailed in Section V-D, concern the quasi-experimental design, single-country sample, incomplete demographic data, and the use of conventional rather than advanced inferential statistics. Future work should extend the evaluation longitudinally beyond a single

semester, incorporate individual-level randomisation where feasible, apply multilevel modelling to account for institutional clustering, and examine artificial-intelligence-driven intelligent tutoring [30] and virtual-reality or digital-twin laboratory extensions [31] of the system architecture presented in Section III-C, particularly for high-voltage and electric-vehicle diagnostic training where physical practice carries genuine safety risk. Emerging guidance on the responsible integration of artificial intelligence into education [45], [46] should inform the design of any such extensions.

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