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Integrating Morphological Analysis and Design of Experiments into First-Year Mechanical Engineering Education*

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This study implements a scalable two-stage project that bridges Morphological Analysis (MA) to Taguchi Design of Experiments (DOE) within an extended Kolb cycle, using a modular spring-powered vehicle as a common platform. Stage 1 targeted configuration selection for mean performance; Stage 2 targeted variance control under noise factors, e.g., payload. Across 168 students organized into 44 teams, evidence shows clear gains in systematic exploration and data-driven experimentation. Formative evidence from staged assignments indicated that the pathway functioned as intended: most teams discriminated performance-critical factors in Stage 1 (best-worst S/N gaps > 5 dB in 31 teams), and a subset achieved variation reduction in Stage 2 (travel-distance standard deviation reduced by 37.5%). In summative trials with random payloads, 33/44 teams reached accuracy rate $\geq$ 90% (median 95.8%), and 34 teams recorded zero lateral offset. Pre/post analysis of the course-feedback survey showed significant gains (nonparametric tests, $p < 0.001$; medium effects) in students' self-efficacy for systematic configuration concept generation and evaluation and for data-driven experimental optimization, alongside improvements in holistic systems thinking and evidence-based reflection, while motivation remained stable over the six-week cycle. Contributions are threefold: (1) an explicit MA $\times$ DOE framework that operationalizes Kolb's cycle for novices; (2) a short, large-enrollment pathway that yields accurate and stable performance while cultivating systematic experimentation; and (3) a reusable, low-cost kit and artifacts. The pathway appears replicable. Brief Stage 2 variance checkpoints and paired pre/post measures may further enhance variance control and evaluation fidelity.

Keywords: first-year mechanical engineering education; experiential learning; project-based learning; morphological analysis; Taguchi method; design of experiments

1. Introduction

1.1 Background and Motivation

In engineering education, lecture-dominated classrooms have often been associated with insufficient student motivation and low retention rates [1]. To address this challenge, many programs have shifted toward the early introduction of engineering design and hands-on projects. Evidence shows that first-year design courses can enhance students' self-efficacy, strengthen professional skills, and positively influence the persistence of underrepresented groups [2]. Introducing design-oriented and project-oriented courses at the outset of the curriculum is regarded as an effective strategy for promoting early development and broadening participation across diverse student populations. While much of the literature has focused on capstone projects, studies such as Aiouache et al. [3] suggest that small-scale design projects in the first or second year are both feasible and beneficial. Even when students' foundational knowledge is limited, they can complete projects effectively and cultivate decision-making skills under appropriate guidance.

Project-based learning (PBL) has thus become a defining trajectory in twenty-first-century engineering education. In mechanical engineering, PBL is valued for coupling theory with practice, enabling students to apply theoretical knowledge to authentic problems and fostering creativity, teamwork, and problem-solving competence [4–6]. Students frequently report heightened interest and motivation when engaged in PBL activities, viewing them as integral to their preparation as engineers [5]. However, implementing PBL at the scale of large cohorts introduces notable challenges, such as ensuring consistent team-level guidance and maintaining project quality. Highly open-ended tasks can also lead students to broaden the scope excessively, making it difficult to achieve depth within limited time. Reviews such as Tekmen-Araci [7] advocate the early integration of creativity training into project-based courses, supported by explicit scaffolds, phased learning steps, and transparent assessment criteria to guide exploration and improve learning effectiveness.

1.2 Experiential Learning as Theoretical Foundation

Experiential learning provides a robust theoretical basis for active pedagogies such as PBL, with Kolb's experiential learning cycle [8–10] being par-

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ticularly influential. The model describes four iterative phases, i.e., Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE), through which learners internalize knowledge and transfer it to new contexts. In STEM education, the model elucidates how design tasks integrate interdisciplinary knowledge and foster authentic problem solving [11]. Nevertheless, a review of 220 studies published between 1995 and 2020 found that, despite the prevalence of experiential activities, only about 37% explicitly grounded their instructional design in experiential learning theory [12]. This indicates a need for more deliberate, theory-informed implementations, especially in large first-year cohorts where consistent learning cycles are harder to sustain.

1.3 Structured Methods for Divergent and Convergent Thinking in Engineering Design

Problem definition and scoping are critical starting points in the engineering design process. Comparative studies by Atman et al. [13] show that expert designers invest significantly more effort in scoping and information gathering than students, who tend to rush to solutions. To address this gap, educators employ creativity techniques such as brainstorming, analogical reasoning, and attribute listing. Morphological analysis (MA) [14] is a structured approach that decomposes a problem into key functions or parameters and enumerates alternative ideas or values, creating a design space that supports systematic exploration and encourages innovative concepts. Recent studies indicate that MA is increasingly used in engineering education to foster creativity and collaborative decision making [15], emerging work also explores MA in combination with large language models [16] to support structured concept generation, highlighting its extensibility as a scaffolding tool.

Verification and optimization are equally essential in engineering design. Design of Experiments (DOE) provides a systematic approach for quantifying the effects of multiple factors and identifying optimal or robust solutions. From foundational efforts in first-year engineering education [17] to experiential learning models in mechanical curricula [18], prior work underscores the feasibility and pedagogical value of DOE in novice settings, while recent studies illustrate the applicability of classical DOE to multi-objective optimization in complex systems [19]. Among DOE methods, the Taguchi approach [20] employs orthogonal arrays to identify dominant quality factors with relatively few trials, reducing variation and improving reliability, and it offers a suitable starting point for novices to develop data-informed decision making.

While MA and DOE each hold educational value, they are typically applied in isolation. In practice, students often approach DOE with a convergence-oriented mindset, focusing narrowly on a limited set of variables without systematically exploring the broader design space. Even when familiar with the parameter-diagram framework, learners may lack strategies for identifying control factors. Therefore, integrating MA prior to DOE addresses this gap. By decomposing the problem and enumerating parameter alternatives, MA enables students to link sub-concepts directly to potential experimental factors and levels, creating a structured pathway from systematic divergence to structured convergence.

When embedded in Kolb's experiential learning cycle, the integration of MA and DOE in this study is implemented as an extended experiential pathway rather than two independent cycles. Students begin with CE and RO by engaging in MA for systematic problem decomposition and divergent concept generation, followed by AC and AE through DOE planning and initial trials. The process then transitions into a second RO→AC→AE sequence, where students analyze experimental results, refine conceptual models, and reapply DOE insights before returning to CE with new validated experience. This extended structure explicitly connects creative exploration to data-driven refinement within a single, continuous learning trajectory, offering a scalable scaffold for large-class project-based learning.

1.4 Research Gap and Objectives

The literature reveals that although Kolb's experiential learning cycle is widely acknowledged, few implementations in engineering education systematically integrate creative divergence, concept evaluation, and robust design within a unified project framework, particularly in large cohorts of novice learners where consistent scaffolding and feedback are more difficult to sustain. Likewise, while MA and DOE are well established individually, documented examples of their combined application within an explicitly structured experiential pathway remain rare.

To address this gap, this exploratory study designs and implements a six-week project using a two-stage, extended experiential framework within a compulsory first-year course, *Introduction to Mechanical Engineering*. The framework adopts a class-level PBL format and uses a self-developed modular spring-powered vehicle kit as a scalable, cost-effective instructional platform, allowing every team to engage with a rich design space while applying quantitative methods for refinement. Each stage follows the same extended experiential pathway described in Section 1.3. Stage 1 focuses on determining the vehicle configuration that maximizes achievable travel distance, and Stage 2 focuses on identifying the parameter settings that achieve robust performance under varying conditions. Both stages maintain the "creative-to-analytical" transition by structuring activities around systematic divergence (MA) and structured convergence (DOE) within Kolb's cycle, while preserving exploratory breadth.

Moreover, this study pursues the following research questions from the class-level perspective, using performance indicators and anonymous, voluntary baseline and exit surveys.

RQ1: *In an instructional setting integrating MA and DOE, do students exhibit measurable gains in (a) systematic configuration concept generation and evaluation, and (b) data-driven experimental optimization?*

RQ2: *Does the project-based process promote holistic systems thinking and evidence-based reflection?*

RQ3: *Does participation in the project positively affect students' interest in mechanical engineering and persistence intention?*

In doing so, this work responds to the pedagogical need for theory-informed, structured, and exploratory design learning in early mechanical engineering education, and generates class-level empirical evidence on how such integration can be effectively operationalized and sustained at scale.

2. Theoretical Framework

2.1 Positioning of MA and DOE in the Extended Kolb Pathway

The instructional design in this study adopts an extended experiential learning pathway mapped onto Kolb's learning cycle [8], as illustrated in Fig. 1. The process progresses continuously from creative divergence to evidence-based convergence, with MA and DOE (Taguchi method) embedded in distinct quadrants of the cycle.

In this mapping, MA is mainly positioned in the RO→AC quadrant, where learners move from reflecting on initial experiences to conceptualizing systematic design alternatives. Through function or parameter decomposition and option enumeration, MA expands the design space and makes decision options explicit, reducing the tendency for premature convergence. DOE, implemented using the Taguchi method, is located in the AC→AE quadrant, where conceptual models are translated into structured experimental plans. By employing orthogonal arrays and signal-to-noise (S/N) analysis, DOE enables students to identify dominant factors and optimal settings with minimal trials, ensuring that design refinements are grounded in empirical evidence.

A key linking mechanism between MA and DOE in this framework is the Parameter Diagram (P-diagram) [20]. The P-diagram organizes information generated during MA into three categories. Control factors are the parameters intentionally varied in the DOE to evaluate their impact on performance. Noise factors are the parameters not directly controlled but expected to cause performance variation. Response variables are measurable outcomes used to quantify system performance. By mapping MA-generated parameter options into a P-diagram, students can systematically determine which parameters should serve as DOE factors and levels, which should be modeled as noise, and which should be measured as responses. This structured translation ensures that DOE inputs are functionally traceable to earlier conceptual exploration, preserving the creative breadth of MA while enabling focused, statistically valid experimentation.

2.2 Application of the Extended Pathway Across Two Stages

As shown in Fig. 1, the extended CE→RO→AC→AE→RO→AC→AE→CE pathway is presented and operationalized through eight sequential nodes ①–⑧, each representing a distinct cognitive-action step in Kolb's learning cycle. Table 1 summarizes each node, its corresponding Kolb phase, its function in the learning pathway, and the specific role it plays in this study.

Accordingly, this eight-node sequence is implemented twice as two stages during the project. Stage 1 applies the pathway to explore and select an optimal configuration at a macro level and Stage 2 applies the same pathway to refine the chosen configuration for robustness, focusing on more

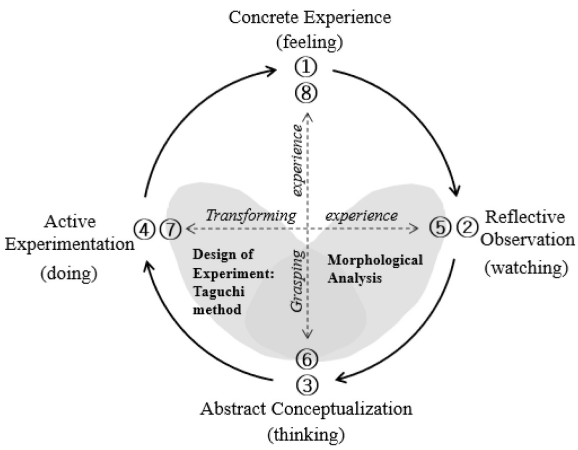


Fig. 1. Extended experiential learning pathway within Kolb's learning cycle.

Table 1. Eight-node extended experiential learning pathway

Node	Function in the pathway	Role in this study
① CE	Establishes the initial, unstructured experience base.	Provides firsthand exposure to the project task and its operational context.
② RO	Organizes and reflects on experience to frame the problem.	Identifies potential variables influencing performance and initial problem boundaries.
③ AC	Structures possible solutions into a coherent design space.	Uses MA to expand configuration alternatives systematically.
④ AE	Plans structured experimentation from conceptual models.	Translates MA outputs into control/noise factors via a parameter diagram and selects an orthogonal array.
⑤ RO	Reviews empirical evidence to assess performance patterns.	Examines trial data for trends, variability, and unexpected outcomes.
⑥ AC	Translates empirical patterns into generalized decision logic.	Applies S/N ratio and main effects analysis to determine robust factor settings.
⑦ AE	Validates decision logic through targeted testing.	Conducts confirmatory trials under defined control and noise conditions.
⑧ CE	Consolidates validated results into transferable knowledge.	Establishes a new experiential baseline to inform the next stage or future projects.

detailed influencing factors. Although the design objectives and parameter granularity differ between stages, the fixed node order provides a consistent learning rhythm, reinforcing the integration of structured divergence (nodes ①–③), evidence-based convergence (nodes ④–⑦), and experiential consolidation (node ⑧).

3. Methods

3.1 Research Context and Participants

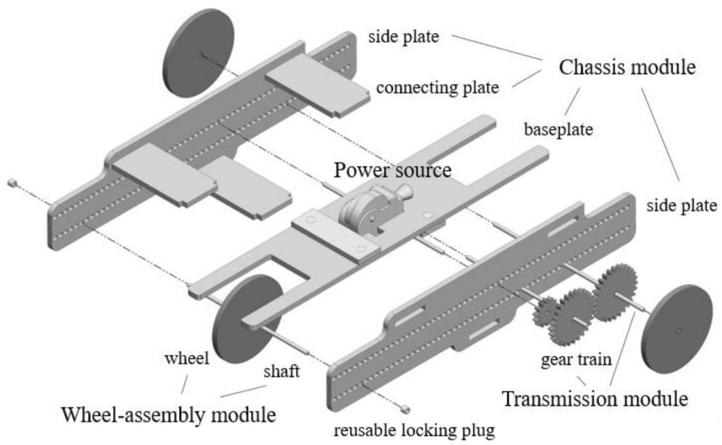
This study was conducted during the Spring 2025 semester as part of a newly established, three-credit compulsory course titled *Introduction to Mechanical Engineering* at a university in Taiwan. The instructional intervention was designed as a class-level exploratory study to examine how Morphological Analysis (MA) and the Taguchi method of Design of Experiments (DOE) could be integrated into a scalable experiential learning framework for novice learners. A total of 168 first-year mechanical engineering students participated, pre-assigned into 44 teams of three to four members. None of the students had prior formal training in engineering design or DOE, although basic statistical concepts had been introduced earlier in the semester. The large enrollment setting provided an appropriate context to evaluate the scalability and coherence of the instructional framework.

Survey responses were collected anonymously on a voluntary basis, and all performance data were recorded and analyzed at the team or class level. No individually identifiable information was obtained during the study.

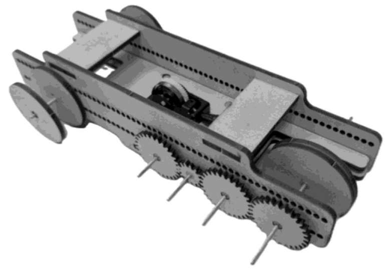
3.2 Instructional Platform and Project Task

A low-cost modular spring-powered vehicle kit was developed as the instructional platform. As illustrated in Fig. 2(a), the kit comprises four major functional modules, i.e., chassis, wheel-assembly, transmission, and torsion-spring power source modules, and fabricated from laser-cut MDF (medium density fiberboard). Chassis module includes a baseplate, two side plates, and connecting plates. The side plates feature dual rows of standardized multi-hole interfaces, allowing adjustable base height and flexible placement of transmission shafts and wheel axles. This design supports rapid reconfiguration and alignment control. Wheel-assembly module provides axles and wheels in three diameters. Reusable locking plugs enable both single- and multi-wheel arrangements, as well as adjustable track widths to accommodate different stability and frictional conditions. Transmission module offers two gear sizes and compatible shafts that can be assembled into varied gear trains. These configurations allow torque delivery to the wheel module with different transmission ratios. Torsion-spring power source utilizes an off-the-shelf unit with adjustable cord-pull preload, serving as the primary energy source for vehicle propulsion.

This modular architecture provides a rich combinatorial design space for systematic variation of drive mode, wheel arrangement, transmission ratio, chassis geometry, and assembly tolerances. It also reduces preparation and logistics overhead in large cohorts, while providing a tangible, manipulable platform for both conceptual and experimental exploration. Fig. 2(b) shows an example configuration with a single front wheel, double rear wheels, a 1:1 transmission ratio, and front-wheel drive. This example demonstrates the flexibility of the kit to produce diverse configurations by altering macro-level parameters. Such flexibility allows students to directly observe how configuration choices, assembly precision, and frictional conditions influence travel performance.



(a) Overview of the kit architecture and modules



(b) An example configuration concept

Fig. 2. Modular spring-powered vehicle kit design.

The project task required each team to determine the optimal spring preload (cord pull length) that would enable the vehicle to travel a randomly assigned target distance under a randomly assigned payload mass, ensuring that the actual travel distance closely matched the target. To structure learning progression and manage cognitive load, the project was divided into two stages. Stage 1 is to determine the macro-level configuration that maximizes travel distance (at least 300 cm) under a fixed preload (50% stroke of cord), with payload mass treated as a noise factor. Based on the determined configuration, Stage 2 is to identify and refine micro-level factors to minimize variance in travel distance under varying payloads while sustaining adequate mean performance.

3.3 Course Planning and Assessment Procedure

During the six-week project, students progressed through two successive applications of the eight-node experiential learning sequence described in Section 2. In Week 1, they were introduced to the project brief and modular vehicle kit, carried out initial assembly and trials to observe performance differences, and identified influential variables to be systematically represented in morphological charts and parameter diagrams; a baseline survey was administered to record initial self-perceptions for later comparison. Week 2 introduced the two-stage design strategy, guiding students to translate morphological chart outputs and identify macro-level factors, e.g., front and rear wheel count, wheel diameter, drive mode (FWD/RWD/4WD), transmission ratio, into control factors and levels for the Taguchi DOE, and arrange them within orthogonal arrays for Stage 1 experimentation. In Week 3, teams analyzed experimental data using S/N ratios (larger-the-better objective) and main effects calculation to determine optimal macro-level settings, validating their results through confirmatory trials to establish a baseline configuration for robustness enhancement. Returning to the start of the cycle in Week 4, students re-scoped the problem to focus on robustness, identifying and parameterizing micro-level factors, e.g., track width, wheel thickness, gear meshing smoothness, center of mass height, ballast position, for DOE targeting variance reduction (smaller-the-better objective). Week 5 was devoted to Stage 2 experimentation, refinement of robustness settings, and development of preload-distance prediction tables through regression analysis, along with a rehearsal for the final timed trials. The project concluded in Week 6 with a summative assessment under randomly assigned target distances and payloads, after which an exit survey was conducted to capture post-project reflections and self-assessments, providing a counterpart to the baseline survey for evaluating changes over the course.

The corresponding course plan is summarized in Table 2, detailing the weekly node coverage, teaching focus, learning activities, and deliverables. The weekly progress deliverables were used to summarize common issues and to discuss and clarify at the start of each subsequent session to maintain coherence and pace.

During the summative assessment in Week 6, each vehicle was required to fit within 25 cm × 15 cm × 10 cm and weigh no more than 250 g. Each team received two independent attempts. For every attempt a computer script randomly generated a target distance D_{target} (400–600 cm in 1 cm increments) and a payload mass (50–150 g in 10 g increments). Within 30 seconds the team consulted its prediction table, set the appropriate spring preload, and released the vehicle from the start line of a 40 cm wide lane without further intervention. After the vehicle stopped, teaching assistants recorded the actual travel distance D_{actual} and the lateral offset L_{offset}. Performance was quantified by the absolute distance error PE and the corresponding accuracy rate AR, listed in Equation (1) and Equation (2) respectively. The higher AR of the two runs was used for grading and for evaluating instructional effectiveness, and 90% of AR is specified as the acceptable threshold.

$$PE = |D_{actual} - D_{target}| \tag{1}$$

$$AR = 1 - PE/D_{target} \tag{2}$$

3.4 Learning Outcomes Assessment

To evaluate the learning outcomes of the instructional intervention, two complementary instruments were administered: a pre-project (baseline) survey in Week 1 and a post-project (exit) survey in Week 6. Participation in both surveys was voluntary and anonymous, and responses were collected using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The survey focused on self-reported competencies and attitudes relevant to the project's intended learning outcomes, enabling group-level comparisons to determine perceived gains over the six-week period.

The course feedback survey consisted of five items Q1–Q5 as listed in Table 3, each aligned with one of the three research questions RQ1–RQ3, a targeted construct, and the corresponding phase(s) of Kolb's experiential learning cycle. Items Q1–Q3 collectively addressed RQ1, which examined whether the integrated use of MA and the Taguchi method could enhance students' systematic configuration design and experimental planning skills. Q1 measured concept generation self-efficacy (CE ↔ AC), Q2 measured concept evaluation self-efficacy (RO ↔ AC), and Q3 measured DOE planning and execution self-efficacy (AC ↔ AE). RQ2 was represented by Q4, which assessed systematic thinking and causal-reasoning confidence (RO ↔ AE). RQ3 corresponded to Q5, which measured students' interest and motivation toward mechanical engineering after participating in the project, representing engagement across the full Kolb cycle.

Table 2. Course plan across six weeks: nodes, teaching focus, learning activities, and deliverables

Nodes	Teaching focus	Learning activities	Deliverables
Week 1 ①–②	Project brief & kit distribution; morphological analysis; parameter diagram	Initial assembly and trial runs; brainstorm configuration options; observe performance differences; construct morphological chart and parameter diagram	Baseline survey; morphological chart
Week 2 ③–④	Two-stage design strategy; macro-level factors affecting travel distance; orthogonal arrays (e.g., L8, L16) and factor arrangement	Formulate Stage 1 problem (objective: larger-the-better); select factors and determine levels; prepare DOE test sheet; conduct Stage 1 experiments under random payload exposure	Stage 1 DOE sheet; experimental data set
Week 3 ⑤–⑧	Objective function and S/N ratio analysis (larger the better); main effects analysis	Compute S/N ratios; identify optimal macro-level factor settings; validate configuration through confirmatory trials	Main effects analysis results; optimal configuration
Week 4 ①–④	Review Stage 1 DOE process; micro-level factors affecting variance; factorial design for robustness enhancement	Formulate Stage 2 problem (objective: smaller-the-better); select factors and determine levels; prepare DOE test sheet; conduct Stage 2 experiments	Stage 2 DOE sheet; experiment data set
Week 5 ④–⑧	S/N ratio analysis (smaller the better); regression-based prediction table; final assessment procedure	Analyze Stage 2 results; determine robustness settings; run preload-distance trials; build prediction table mapping preload to distance under varying payloads	Robustness settings; prediction table
Week 6 ⑧	Summative assessment; project journey review	Apply prediction table to meet random target distance and payload; complete two timed trials; reflect on project process	Assessment results; exit survey

Table 3. Mapping of research questions (RQ1–RQ3) to course feedback survey items (Q1–Q5)

RQ	Item	Description (5point Likert scale: 1 = strongly disagree, 5 = strongly agree)	Measured construct	Kolb's cycle phases
RQ1	Q1	*When designing a springpowered vehicle, I can apply systematic creativeproblemsolving skills to generate design concepts instead of relying mainly on intuition or adhoc brainstorming.*	Concept generation selfefficacy	CE ↔ AC
	Q2	*A spring-powered vehicle can be configured in many ways; I know how to evaluate these alternatives effectively to select an appropriate design.*	Concept evaluation selfefficacy	RO ↔ AC
	Q3	*I know how to plan and carry out experiments to identify and analyze the factors that influence the performance of a springpowered vehicle.*	DOE planning & execution selfefficacy	AC ↔ AE
RQ2	Q4	*I can solve engineering problems by applying systematic thinking and methods.*	Systematic thinking/ causalreasoning confidence	RO ↔ AE
RQ3	Q5	*The "Introduction to Mechanical Engineering" course has increased my enthusiasm for learning mechanical engineering.*	Interest & motivation	Full cycle

In addition to the quantitative survey data, students' written reflections from their project reports were subjected to a targeted qualitative analysis. Statements were coded according to their relevance to the constructs measured in Q1–Q5, enabling triangulation between the quantitative Likert-scale results and qualitative insights. Subsequent statistical analyses employed non-parametric tests and effect size measures to compare baseline and exit survey data at the group level, providing a robust basis for interpreting learning gains.

4. Results and Discussion

4.1 Two-Stage Assignment Data Analysis

The two-stage assignment data, collected as part of weekly progress submissions, provide an overview of how student teams progressed along the planned learning pathway. Stage 1 data were submitted in Week 3 at node ⑥ (AC), and Stage 2 data were submitted in Week 5 at the same node. These submissions represent the state of each team's work at the time of submission, rather than their final designs. While many teams continued refining their work after submission, these later improvements were not collected. In some cases, the Stage 2 submissions already reflected partial optimization based on Stage 1 results, whereas the full Stage 2 robust experimental trials had not yet been completed at the time of submission.

In Stage 1, 41 teams submitted complete assignments. Among these, 35 teams achieved an average travel distance greater than 300 cm, satisfying the stage requirement. For the S/N ratios, 23 teams exhibited a difference of more than 10 dB between their best and worst configurations, and 31 teams achieved a difference greater than 5 dB. This indicates that, by the node ⑥ of Stage 1, most teams had identified key design factors influencing performance and were able to use data to evaluate the quality of configuration combinations. In Stage 2, 39 teams submitted complete assignments. After implementing their robust parameter-setting experimental designs, 35 teams still achieved an average travel distance greater than 300 cm. Notably, 12 teams showed a substantial reduction in the standard deviation of travel distance, with the average value decreasing from 158.20 cm in Stage 1 to 98.85 cm in Stage 2, i.e., an average reduction of 37.5%. This indicates that, by the node ⑥ of Stage 2, fewer than one-third of teams had identified and controlled micro-level factors affecting variation.

The lower-than-expected number of complete submissions in both stages, together with incomplete achievement of Stage 2 objectives for some teams, points to potential constraints in the course process. Although there was one additional week between Stage 2 submission at Week 5 (node ⑥, AC) and the final assessment at Week 6 (node ⑧, CE) for further refinement and practice, not all teams appeared to have fully leveraged this period to complete robust parameter-setting trials or reduce performance variation. Possible contributing factors include the challenge of mastering and applying newly introduced experimental design skills within a short course cycle, differences in team-level engagement during the refinement week, and the complexity of identifying micro-level variation-inducing factors. A plausible pattern is that some teams retained a Stage-1 mindset, adjusting factor levels to narrow variation, rather than formulating a distinct robustness-focused plan. This pattern suggests that more explicit problem definition and instructional guidance at the transition between stages could better direct students toward exploring and implementing robustness-focused experimental strategies.

When interpreted in relation to RQ1, these results indicate that while most teams successfully identified key performance factors during the configuration design stage (Stage 1), fewer were able to demonstrate systematic robustness enhancement in Stage 2 within the given course timeframe. This highlights the potential need for refined pacing and targeted instructional interventions, e.g., brief variance-framing checkpoints between Weeks 4–5, to strengthen the transition from configuration optimization to robustness-oriented experimentation.

4.2 Final Assessment Results

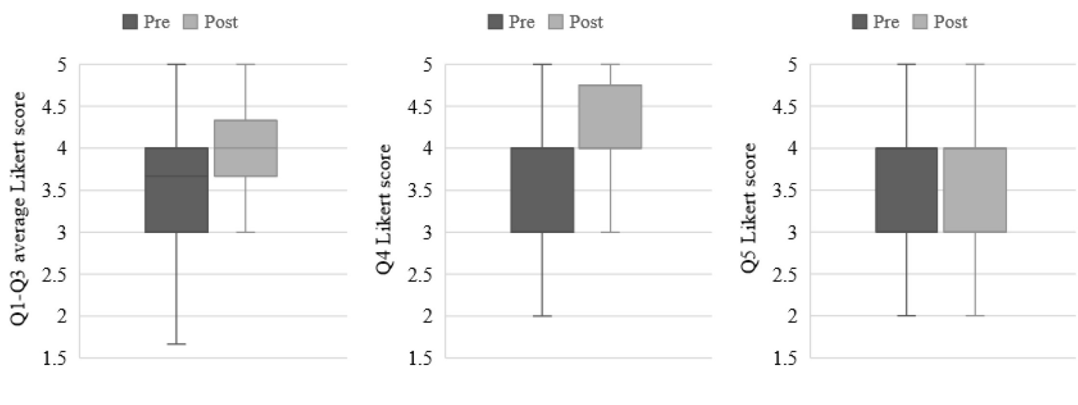
A total of 44 teams completed the final summative trial at node ⑧ (CE), where their performance was evaluated using three indicators presented in Section 3.3. For lateral offset L_{offset}, 34 teams achieved a value of 0 cm, resulting in a highly skewed distribution with a large cluster at zero and a long right tail. This pattern indicates that the majority of teams attained stable lane keeping under the assessment conditions. For distance error PE, the median was 20.0 cm with an interquartile range IQR of 45.75 cm (the first quartile = 11.75 cm, the third quartile = 57.50 cm), reflecting considerable variation in longitudinal precision. These differences are likely attributable to variations in conceptual design quality, propulsion system efficiency, and the degree to which experimental planning was systematically executed. For accuracy rate AR, the median was 95.8% (IQR = 7.7%) with a mean of 91.8%. 24 teams achieved $AR \geq 95\%$, and 33 teams reached $AR \geq 90\%$, demonstrating that most teams were able to integrate their design solutions with data-driven verification to deliver performance that met or exceeded the target threshold. Analysis of the randomly assigned payloads showed that heavier loads tended to degrade distance accuracy, whereas lateral offset appeared unaffected, suggesting that load variation primarily impacted propulsion performance rather than lateral stability.

These results indicate that, by the end of the course, most teams successfully integrated design decisions with experimental verification to achieve the target accuracy level while maintaining lateral stability under varying load conditions. The high proportion of zero-offset outcomes suggests that lane-keeping stability was effectively addressed during the design process. However, the substantial spread in PE values, even among teams with high AR, reflects that longitudinal precision was more susceptible to variations in design and operational control. This pattern implies that while the staged learning pathway effectively supported the attainment of baseline performance requirements, reinforcing precision-oriented experimental planning and factor control, particularly in the presence of external load variations, could further enhance robustness in future course iterations.

4.3 Course Feedback and Qualitative Insights

The course feedback survey achieved a high baseline response rate (157/168, 93.5%) and a satisfactory post-course return rate (110/168, 65.5%), providing a reliable basis for statistical comparison. Given the unpaired nature of the datasets, the Mann-Whitney U test was applied, with effect sizes estimated via Cliff's δ and their 95% confidence intervals (CIs) obtained through bootstrapping. Internal consistency of the five-item Likert scale was acceptable (Cronbach's α = 0.83), and remained high for the three items under RQ1 (Q1–Q3) at α = 0.79.

Descriptive results shown in Fig. 3 indicated that median scores for Q1–Q3 increased from 3.67 to 4.00, with the IQR narrowing from 1.00 to 0.67, suggesting a higher central tendency and reduced variation after instruction. Q4 rose from 3.00 to 4.00 with the IQR reducing from 1.00 to 0.75,



(a) Q1–Q3 average (b) Q4 (c) Q5

Fig. 3. Box plots of baseline and exit surveys Likert (5-point) responses.

Table 4. Mann-Whitney U test and Cliff's δ effect sizes for course feedback survey

Likert Question	**U**	**p**	**Cliff's δ**	**δ 95% CI**	**Interpretation***
Q1 (Concept generation)	6150.0	1.56e–05	0.288	[0.167, 0.410]	Small
Q2 (Concept evaluation)	6496.0	1.31e–04	0.248	[0.127, 0.365]	Small
Q3 (DOE planning & execution)	6529.5	1.99e–04	0.244	[0.121, 0.369]	Small
Q4 (Systematic thinking)	5561.5	1.11e–07	0.356	[0.236, 0.475]	Medium
Q5 (Interest and motivation)	8983.0	0.554	–0.040	[–0.175, 0.097]	Negligible
Q1–Q3 composite	5215.5	2.16e–08	0.396	[0.269, 0.522]	Medium

* Effect size follows ref. [24]: $|\delta| < 0.147$ = negligible, 0.147–0.33 = small, 0.33–0.474 = medium, and ≥ 0.474 = large.

reflecting gains in systematic thinking and causal reasoning. Q5 maintained a median of 4.00 with minimal IQR change, implying stable motivation levels throughout the course.

Inferential testing results, listed in Table 4, revealed statistically significant improvements for Q1–Q3 and Q4 (all $p < 0.001$), with effect sizes in the small to medium range. For RQ1, each individual item Q1–Q3 improved significantly ($p < 0.001$) with small effect sizes ($\delta \approx 0.24$–0.29), while the composite Q1–Q3 score achieved a medium effect size ($\delta = 0.396$). For RQ2, Q4 improved significantly with a medium effect size ($\delta = 0.356$). For RQ3, Q5 exhibited no significant change ($p = 0.554$, $\delta = -0.04$), suggesting that skill-oriented gains were achieved without a corresponding shift in intrinsic interest over the short course duration.

These quantitative patterns suggest that skill-related competencies, particularly those directly targeted by the course's structured MA $\times$ DOE framework, can be effectively enhanced within a short instructional period, as reflected by the significant gains in Q1–Q4. The concurrent reduction in score dispersion further indicates a convergence in students' self-perceived competence, likely due to the homogenizing influence of shared experiential cycles and guided design-experiment protocols. In contrast, the stability observed in Q5 implies that intrinsic interest and motivation may require more sustained engagement and broader contextual reinforcement to shift perceptibly, a tendency consistent with prior findings in engineering education [25].

Furthermore, qualitative analysis of the 44 end-of-project reports yielded patterns consistent with the course feedback survey results, providing additional context on how the learning pathway was enacted. In the CE phase, common observations concerned variability sources such as floor friction, wheel alignment, and heavy payload vs. long distance combinations, which were reframed as design constraints. Representative excerpts included "*different floor conditions led to divergent results*" and "*the vehicle often veered, so wheel friction had to be adjusted.*" RO was frequently characterized by a shift from intuition to evidence-based reasoning and by iterative resolution of performance discrepancies, as indicated by "*verification with data taught me to reason systematically*" and "*failures prompted root-cause searches and design adjustments.*" In AC, repeated references to orthogonal arrays, S/N ratios, and stability metrics demonstrated the formulation of explicit decision rules from empirical patterns, for example, "*after comparing S/N ratios, the optimal configuration was selected*" and "*standard deviation clearly distinguished consistent settings.*" AE emphasized the operationalization of these abstractions into reproducible protocols, reflected in "*a full-factor micro-tuning was initiated*" and "*tests were standardized. . . to suppress extraneous variation.*" Collectively, these qualitative accounts complement the statistical comparisons by illustrating the practical behaviors underpinning the observed learning gains.

4.4 Discussion and Implications

Findings from performance metrics, survey responses, and report excerpts converge to indicate that the MA $\times$ DOE framework can embed systematic design and experimentation habits in a first-year, large-class setting. The structured learning pathway enabled most teams to identify key performance factors early, convert empirical observations into DOE-based decision criteria, and operationalize these into reproducible testing protocols. This alignment between experiential observations and statistical reasoning demonstrates the framework's capacity to scaffold novice learners toward evidence-based engineering practice without sacrificing methodological rigor. Axial-distance accuracy (AR) results in the summative trial, with 33 teams achieving $\geq 90\%$, which further indicates that stability under varying conditions reached an acceptable range for most participants.

At the execution level, the Stage 1 to Stage 2 transition revealed a recurring conceptual gap: shifting from a design focus that emphasized elevating baseline performance, while implicitly addressing variation through S/N ratio evaluation, to one that required explicitly prioritizing consistency under designated noise factors. Whereas Stage 1 tuning helped teams identify influential factors and achieve higher mean outcomes, Stage 2 demanded a reframing of objectives so that robustness became the dominant design goal. However, the limited measurable variation reduction and the 11 teams below the *AR* threshold suggest that variance-control strategies were not uniformly assimilated, potentially due to insufficient noise-factor recognition, persistence of performance-oriented tuning habits, or underuse of iterative verification during refinement.

These patterns highlight that cultivating robustness thinking requires more than statistical tools. It calls for explicit framing of noise-induced risks, direct mapping between S/N or standard deviation metrics and physical design margins, and structured opportunities to validate such mappings during development. Embedding variance-focused deliverables, stratified performance analysis, and guided design-translation exercises in Weeks 4–5 could strengthen Stage 2 outcomes. More broadly, the findings indicate that cultivating a robustness-oriented problem frame is not an incidental outcome but a deliberate pedagogical goal, particularly when novices must navigate competing performance objectives within compressed development cycles. Embedding this mindset early in the design curriculum equips learners to prioritize consistency under variability, transfer robustness principles across contexts, and make disciplined trade-offs between optimality and reliability, which are the capabilities essential for sustainable engineering practice.

Overall, the findings align directly with the three research questions. For RQ1, both process behaviors and outcome metrics affirm that the MA $\times$ DOE pathway effectively nurtured systematic design exploration and data-driven experimentation: in Stage 1, most teams identified performance-critical factors (31 teams > 5 dB of best-worst S/N gaps), and a subset in Stage 2 achieved measurable variation reduction (–37.5% on average), while at the summative trial 33 of 44 teams reached AR $\geq$ 90%. These outcomes were reinforced by significant survey gains on Q1–Q3 ($p < 0.001$, $\delta \approx 0.24$–0.29; composite $\delta = 0.396$), evidencing structured learning gains despite uneven translation to robustness control within the six-week cycle. For RQ2, Q4 improved significantly ($p < 0.001$, $\delta = 0.356$), supported by report evidence that students reframed variability sources as design constraints, codified decision rules with DOE tools, and operationalized these into reproducible trials, demonstrating growth in reflective, systems-level reasoning even as the Stage 1$\rightarrow$2 robustness shift remained a key instructional inflection point. For RQ3, no significant motivational change was detected (Q5: $p = 0.554$, $\delta = -0.040$), consistent with a stable, already-elevated baseline and the short, skill-intensive timeframe. In summary, the study provides affirmative support for RQ1 and RQ2, while RQ3 highlights the boundary conditions of short-cycle interventions, pointing to robustness reframing and longitudinal motivation scaffolds as priorities for future refinement.

5. Limitations

Some limitations of this study stem from the exploratory nature of this first-run course design and evaluation. The course was implemented within a single department, at one academic level, over a fixed six-week period with predetermined modular-kit specifications. While these boundary conditions inevitably limited the diversity of design configurations and operational variables that could be explored, they also ensured comparability, manageability, and fairness across a large cohort. Standardization allowed all teams to engage with the MA $\times$ DOE framework on an equitable basis, lowering barriers to entry and enabling the instructional emphasis to remain on systematic design reasoning and variance analysis rather than on resource disparities. Future iterations may relax kit constraints or extend scheduling flexibility to open opportunities for more diverse experimentation while preserving this baseline of stability.

The performance evaluation focused on axial distance accuracy and lateral deviation under randomly assigned payload conditions as summative indicators. Although these aggregated end-point measures aligned with course objectives and enabled comparability, they did not capture finer-grained learning curves, intermediate design iterations, or performance variance attributable to specific noise-factor classifications. Nevertheless, this focus also represented a pedagogically intentional simplification, helping novice learners anchor their decision-making to clear, quantifiable outcomes. Subsequent refinements could incorporate stratified analysis by payload level, intermediate prototype tracking, and more granular variance decomposition to deepen insights into robustness strategies.

At the execution level, the Stage 1 to Stage 2 transition was supported only through standard instructional sessions and a single formative submission checkpoint. While this limited intermediate opportunities for variance-focused design verification, it also revealed that even with minimal scaffolding, students were able to internalize key aspects of robustness thinking. Future iterations may benefit from additional checkpoints and guided interventions, but the present design demonstrated the feasibility of embedding systematic design habits in a compressed large-class format.

From a data-collection perspective, the post-course survey had a lower response rate and was administered as an unpaired measure, constraining the resolution of attitudinal change analysis. Still, the convergence between quantitative and qualitative findings provides a coherent picture of learning outcomes and validates the core pedagogical pathway. Future improvements such as paired pre/post-course measurements, strategies to increase survey participation, and more probing complementary methods, including focus groups and semi-structured interviews, would further strengthen the robustness and explanatory depth of the attitudinal evidence and help illuminate mechanisms underlying the observed gains.

Overall, while the study's scope was necessarily bounded by its first-run and large-class context, these same boundaries offered a stable and scalable platform for embedding the MA $\times$ DOE framework into introductory engineering curricula. Rather than undermining its contributions, the constraints demonstrate that even under limited time, standardized resources, and fixed instructional ratios, it is possible to cultivate systematic design and experimentation habits at scale. Future iterations can leverage these lessons to progressively expand flexibility, deepen robustness evaluation, and strengthen transferability, thereby turning initial constraints into a roadmap for sustainable instructional innovation.

6. Conclusions

This study designed and evaluated a two-stage project pathway that integrates morphological analysis and Taguchi's design of experiments within Kolb's experiential learning cycle in a large, first-year mechanical engineering course, using a modular spring-powered vehicle kit as the common experimental platform. Stage 1 guided configuration selection toward mean performance, whereas Stage 2 targeted variance control under noise factors, e.g., payload, enabling a structured transition from conceptual exploration to robustness-oriented refinement with uniform, hands-on baselines.

Synthesis with the research questions. For RQ1, converging process and outcome evidence shows clear gains in systematic exploration and data-driven experimentation: most teams discriminated performance-critical factors in Stage 1 (best-worst S/N gaps >5 dB for 31 teams), and a subset realized measurable variance reduction in Stage 2 (mean standard deviation lowered by about 37.5%). These behavioral indicators are consistent with the survey: pre/post comparisons for Q1–Q3 showed significant improvements (all $p < 0.001$) with a medium composite effect (Cliff's $\delta = 0.396$). At the summative trial under random payloads, 33/44 teams achieved AR $\geq$ 90% (median AR = 95.8%), with 34 teams recording zero lateral offset, demonstrating effective integration of design decisions and verification. For RQ2, survey and artifact evidence indicate significant gains in systematic/reflective reasoning (e.g., Q4, $p < 0.001$, $\delta = 0.356$ medium effect), reflected in students' increasing use of structured experimentation to justify configuration and settings. For RQ3, motivation did not change detectably over the short, skill-intensive six-week cycle, while the modular kit translated abstract concepts into tangible action and supported scalable, fair evaluation.

Limitations include implementation within a single institution and cohort, fixed kit specifications, and unpaired survey measures, which constrain generalizability and the resolution of attitudinal inferences.

In conclusion, the study contributes at three levels: theoretically, it elucidates how an MA $\times$ DOE framework operationalizes Kolb's cycle and strengthens robustness-oriented thinking through explicit scaffolding; instructionally, it shows that a staged pathway can deliver high accuracy and stability at scale within six weeks while enabling factor screening and variation reduction; and practically, it offers a reusable modular kit and ready-to-use artifacts suited to large-enrollment constraints. Beyond this cohort, the pathway and kit can be replicated in other introductory contexts; brief variance-focused checkpoints in Stage 2 and paired pre/post measures would further sharpen variance control and evaluation fidelity.

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