

Development of a physical-digital learning environment for rotational motion transmission in engineering education

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This study presents the design and evaluation of a physical-digital learning environment for teaching rotational motion transmission in introductory engineering education. The environment integrates SimulaGear, an interactive digital simulation for analyzing gear systems, with a physical-IoT experimental system composed of a 3D-printed gear mechanism, infrared sensors, ESP32-based data acquisition, Message Queuing Telemetry Transport communication, and real-time visualization through Node-RED dashboards. A quasiexperimental pretest-post-test design was implemented with 37 first-year engineering students enrolled in introductory physics courses. The control group worked exclusively with the SimulaGear digital simulation, whereas the experimental group participated in a physical-digital experience that combined SimulaGear with the physical-IoT experimental system. Conceptual understanding, student engagement, and technology acceptance were evaluated using a conceptual test, the Utrecht Work Engagement Scale for Students, and a survey based on the technology acceptance model. Results showed that both groups improved their conceptual understanding after the intervention, with the group that used the physical-digital system showing a specific significant improvement in transmission ratios in multiple-gear systems. In addition, the physical-digital experience produced significant gains in vigor and overall engagement, while the digital-only experience did not show significant changes in engagement. Technology acceptance was high in both groups, but significantly higher in the experimental group. These findings suggest that integrating physical-IoT systems with digital simulations can strengthen students' engagement and technology acceptance while supporting the interpretation of complex mechanical configurations through the comparison of theoretical predictions and real-time experimental data.

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I. INTRODUCTION

When conducting research on a physical phenomenon, the parameters are individually controlled when acquiring experimental data in order to observe how the system is affected. Experiments are an essential component of physics education and, in general, teachers use experiments to verify and demonstrate the theoretical content taught in class [1]. Observation is a fundamental part of learning in the field of physics, and it has been identified as a core element in problem solving within real-world scenarios in mechanics, since eye tracking makes it possible to analyze and understand new information [2]. In the literature, the use of simulators such as PHET has

been implemented worldwide as a virtual laboratory for physics learning, where students have the opportunity to analyze interactive visualizations and animations that facilitate the learning of basic concepts. The use of this simulator in the classroom is recommended to promote active learning in educational activities [3].

Augmented reality can be combined with textbook knowledge and previous activities to enhance the learning environment, allowing students to interact directly with a specific environment in real time for physics learning. This technology represents a promising field with significant potential for future development [4]. Experimentation at the higher education level through laboratories reinforces the concepts learned in class and promotes students' critical thinking compared with those who only attend theoretical classes [5]. However, student learning does not depend solely on the experiments that can be conducted in the laboratory; it also depends on the depth of theoretical instruction provided by teachers. This was studied and compared across several groups from public and private schools in Indonesia, where, despite having fewer

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laboratories, private high school students achieved better results in evaluation exams on biology topics [6].

Implementing digital work environments in the classroom is not a simple task for teachers. There are ecosystems called Go-Lab, which provide a preconfigured setup that users can adjust according to their needs and the topic to be addressed during class. Despite this, teachers often prefer to create environments from scratch so that they can be tailored more precisely to their particular needs [7]. During the COVID-19 pandemic, it became necessary to use digital physics laboratories to promote experimental work. These technologies were positively accepted by users as an alternative for distance learning, emphasizing the acquisition and analysis of information obtained through digital tools [8].

Remote laboratories allow experimentation and interaction with physical phenomena using Internet of Things technology, with access through laptops, tablets, or even mobile phones. In physics, several practices were created on free fall, Hooke's law, and projectile motion, establishing connectivity through hardware and software, and offering students remote interaction [9]. Another technology is digital twins, which consists of a simulation model synchronized with an operating machine; when the digital environment is changed or modified [10], the same movement is performed by the machine in real time. This technology can also be applied in the context of physics laboratories.

In introductory engineering physics, rotational motion transmission in gear systems provides a suitable context for connecting mathematical models, digital simulation, and physical system behavior. However, students may struggle to interpret how angular velocity, gear radius, transmission ratios, and rotation direction interact across multigear systems, especially when moving from idealized representations to physical mechanisms. The main contribution of this study lies in the design and evaluation of a physical-digital learning environment for rotational motion transmission, comparing its effects with a digital-only experience in terms of conceptual understanding, student engagement, and technology acceptance. In this way, the study provides evidence on how the integration of a physical-IoT experimental system with a digital simulation may support students' learning experience and shape their acceptance of educational technologies for modeling mechanical systems in introductory engineering courses.

Modeling constitutes essential practice in engineering education, as it makes it possible to represent systems, analyze relationships between variables, anticipate behaviors, and make informed decisions before intervening in, building, or modifying real systems. In this sense, mathematical modeling functions not only as a professional tool for engineers but also as an instructional strategy to promote applied reasoning in the classroom. According to Lyon and Magana [11], mathematical modeling in

engineering education has been studied as a means to develop problem-solving strategies, implement learning activities, and assess thinking processes characteristic of engineering practice. Along similar lines, Merck *et al.* [12], argue that engineering students need to engage in mathematical modeling tasks to strengthen their learning through the application of mathematics to authentic problems and real design situations, and they note that technological resources can support these types of experiences. In addition, Dominguez *et al.* [13], highlight that the use of modeling fosters the integration of physics and mathematics in science, technology, engineering, and mathematics education, which is especially relevant for designing experiences in which students connect scientific concepts, mathematical representations, and application-based situations. Therefore, promoting students' ability to construct, interpret, and contrast models from the early stages of their education is relevant for strengthening the connection between scientific principles, mathematical relationships, and engineering problems.

Within this framework, laboratories have historically occupied a central place in engineering education, as they allow students to interact with real systems, manipulate instruments, collect data, and relate theory to empirical experience [14]. Feisel and Rosa [15] emphasize that the undergraduate engineering laboratory should not be understood merely as a space for verifying theoretical content, but rather as a formative environment in which students develop skills related to experimentation, data analysis, design, work with real equipment, and understanding the limitations of physical systems [16,17]. From this perspective, the physical laboratory provides a dimension that can hardly be fully replaced: material interaction with the phenomenon, including uncertainty, measurement errors, tolerances, friction, losses, and nonideal conditions [18].

At the same time, the development of virtual laboratories and digital platforms has expanded teaching possibilities in science and engineering. These environments allow phenomena to be represented, parameters to be manipulated, experiences to be repeated, variables to be visualized, and scenarios to be explored that may be costly, complex, or difficult to control in a physical laboratory. According to Reeves and Crippen [19], research on virtual laboratories in university science and engineering courses has focused mainly on evaluating individual changes in content knowledge, which opens opportunities to broaden the theoretical and methodological approaches in this field. Complementarily, Li *et al.* [20] report that virtual laboratories have been widely incorporated into engineering education and that there is evidence of their effect on student performance, although their implementation still needs to be studied across different contexts and modalities.

Nevertheless, the value of virtual laboratories does not imply that physical experience loses relevance. Rather, literature points to the relevance of integrating both approaches. de Jong *et al.* [18] state that students can

investigate scientific phenomena both in physical laboratories, which promote interaction with the material world, and in virtual laboratories, which take advantage of the potential of simulations. These authors propose contrasting the value of both types of inquiry and recommend combining them to strengthen learning in science and engineering. This idea is particularly relevant for teaching models, since the digital environment can represent the idealized behavior of a system, while the physical environment allows students to observe deviations, limitations, and uncertainties inherent to real behavior.

From this perspective, a physical-digital proposal can be especially appropriate for helping novice students to work with the distinction between a theoretical model and a real system. On a digital platform, students can manipulate variables, identify functional relationships, and observe predictions under controlled conditions. In the physical system, by contrast, they can measure, compare, and recognize that real behavior does not always coincide exactly with the idealized representation. This comparison favors a more robust understanding of modeling, because it shifts learning from the simple application of equations toward the analysis of assumptions, scope, discrepancies, and conditions of validity of the model [18,21]. In this study, gear systems are adopted as an introductory mechanical context because they allow students to work with an observable, manipulable, and mathematically modelable system, in which they can move between the idealized representation of system behavior and comparison with measurements obtained from a physical device. This choice is consistent with studies that have used gears as visual and tangible representations for learning mathematical concepts [22], as well as with recent research that employs digital models of gear systems to represent, measure, and analyze their physical behavior [23].

Beyond conceptual learning, it is important to analyze how students accept and value these types of educational technologies. At this point, the technology acceptance model (TAM) offers a relevant framework for studying perceptions related to perceived usefulness, perceived ease of use, attitude toward use, and intention to use technology. According to Granić and Marangunić [24], TAM has become one of the most widely used models for analyzing technology acceptance in educational contexts, particularly in studies focused on students and higher education. In the Ibero-American context, Cabero-Almenara and Pérez [25] validated the TAM model to study the adoption of augmented reality resources through structural equation modeling, demonstrating its relevance for analyzing emerging educational technologies. More closely related to the present study, Estriegana *et al.* [26] used an extension of TAM to study students' acceptance of an online environment that integrated virtual laboratories, interactive activities, educational videos, and a game-based methodology.

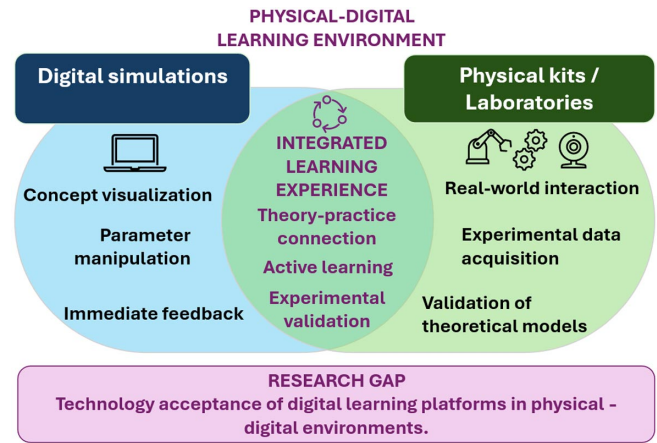


FIG. 1. Conceptual representation of the proposed physical-digital learning environment and the associated research gap.

Likewise, Hernandez *et al.* [27] used TAM to evaluate the acceptance of a didactic resource based on digital shadow in control engineering courses, which reinforces the relevance of this model for analyzing educational technologies that articulate digital representation, engineering systems, and applied work. Taken together, these studies justify the use of TAM in the present study—not only to evaluate the acceptance of a digital platform but also to compare how such acceptance changes when the experience is implemented exclusively digitally or integrated with a physical laboratory.

Based on the reviewed literature, a gap is identified regarding the analysis of physical-digital experiences from the perspective of technology acceptance as shown in Fig. 1. Although there are studies on mathematical modeling in engineering, physical laboratories, virtual laboratories, and technology acceptance, further evidence is still needed on how the acceptance of a digital platform changes when it is implemented alone compared with an implementation that integrates it with a physical laboratory. This question is relevant because technology acceptance does not depend solely on the digital interface, but also on the pedagogical experience in which it is embedded. In other words, the same platform may be perceived differently if it is used as an independent digital resource or if it is articulated with an experimental experience that allows students to contrast theory with the behavior of a real system.

Based on this gap, the present study examines a physical-digital learning environment that integrates a digital simulation with an instrumented physical gear system. The purpose is to analyze how this integration supports students' conceptual understanding, engagement, and technology acceptance in the context of rotational motion transmission. The following section describes the design and development of the proposed learning environment.

II. METHODS

A. Design and development of the physical-digital learning environment

1. SimulaGear digital platform

The digital component consisted of a simulation environment called SimulaGear, developed by the research team specifically as an educational tool for the study of rotational motion transmission systems. The application was designed to facilitate the visualization and manipulation of kinematic relationships in gear trains through interactive simulations. The simulation interface is presented in Fig. 2.

The digital simulation allows users to modify parameters associated with motion transmission, including input angular velocity and gear radii. In addition, it is possible to study systems ranging from two to four coupled gears. The system provides immediate visual and numerical feedback on the propagation of angular velocity and the direction of rotation among interconnected gears. The behavior of rotational transmission was modeled using kinematic relationships based on gear dimensions and angular velocity propagation between gears. Through this environment, students can analyze how variations in gear dimensions affect transmission ratios and the rotational behavior of the system.

To use SimulaGear, students first select a configuration of two, three, or four gears, enter the radius of each gear, and set the angular velocity of the first gear, which acts as the driving gear. Based on these values, the simulation automatically calculates the angular velocity of the remaining gears and displays the results in revolutions per minute (rpm). The direction of rotation is also represented during the simulation, with each interconnected gear rotating in the opposite direction to the previous one. The interface allows students to play, pause, and restart the simulation to observe the behavior of the system using the entered values.

The simulation was designed as an interactive learning environment in which students can modify transmission configurations, explore rotational behavior under different

conditions, and analyze the kinematic changes generated in real time. The use of SimulaGear aims to facilitate the conceptual interpretation of rotational transmission phenomena through the dynamic and interactive visualization of abstract mechanical relationships.

The graphical representation uses a fixed arrangement of the gears. Therefore, although students can modify the gear radii, the visual dimensions of the gears do not change proportionally on the screen. The entered values are used to calculate the angular velocities, while the animation allows students to observe the motion and direction of rotation of the system.

2. Physical-IoT experimental system

The physical component of the proposal consists of a gear kit manufactured through 3D printing and instrumented with infrared sensors for measuring angular velocity. The system was designed to enable the analysis of different configurations of interconnected gears with varying pitch diameters and transmission ratios. Figure 3 shows the instrumented physical system used.

The experimental system incorporated a real-time monitoring architecture consisting of

- Infrared sensors,
- an ESP32 microcontroller,
- Message Queuing Telemetry Transport communication,
- and a visualization interface developed in Node-RED.

The general data acquisition and visualization architecture used in the system is presented in Fig. 4.

The sensors measure the angular velocity of each gear in rpm, allowing observation of how angular velocity is transmitted within the system during operation. The data obtained are transmitted wirelessly and visualized in real time through dashboards accessible from computers and mobile devices. The real-time visualization of angular velocities using Node-RED is shown in Fig. 5.

The system allows users to work with configurations of one, two, three, and four interconnected gears with

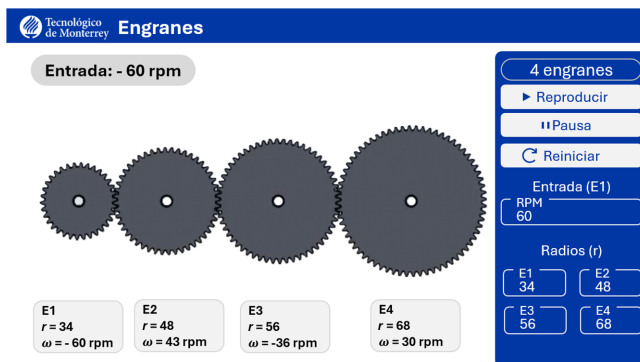


FIG. 2. Digital simulation environment.

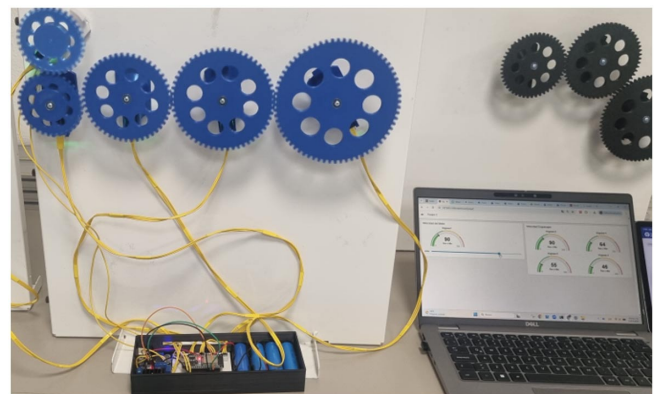


FIG. 3. Physical-IoT experimental system.

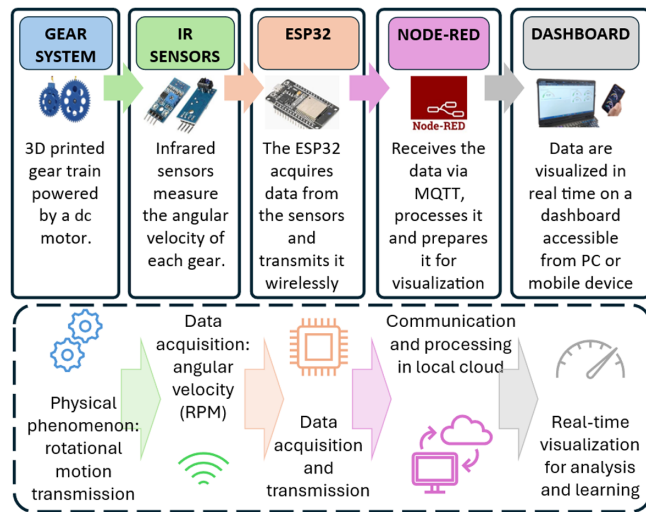


FIG. 4. Data acquisition and visualization architecture used in the physical-IoT system.

different pitch diameters, enabling the experimental analysis of transmission ratios and rotation direction in different mechanical configurations. Some of the configurations used during the intervention are presented in Fig. 6.

The interface developed in Node-RED allows the simultaneous visualization of the angular velocities of the different gears, facilitating the comparison between theoretical predictions obtained through the digital simulation and experimental data generated by the physical system. In this way, the information measured by the sensors is not presented as an isolated result, but rather as part of an analytical process in which students can contrast the expected behavior of the system with its actual operation.

This integration of sensors, IoT technologies, and real-time visualization turn the experimental system into a hybrid physical-digital environment. In this environment, students interact with physical mechanisms while

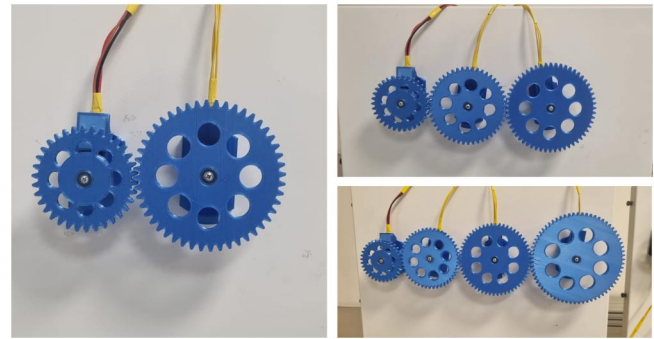


FIG. 6. Gear train configurations used during experimental activities.

observing engineering data generated during system operation, fostering a more integrated understanding of the theoretical model, the digital simulation, and the experimental evidence.

Figure 7 compares the rotational speed values obtained with SimulaGear and the physical-IoT system for a four-gear configuration. The input speed was set to 60 rpm, and the same gear radii was used in both environments to reproduce equivalent transmission conditions. The results show a close correspondence between the model predictions generated by SimulaGear and the real-time experimental data collected through the physical-IoT system, with relative errors ranging from 0.00% to 3.57%. These results illustrate how the physical-digital environment enables students to compare simulated behavior with experimental measurements. In this sense, the physical-IoT system was designed not only as a measurement platform but also as an educational environment aimed at promoting the interpretation, analysis, and experimental validation of motion transmission behavior in rotational mechanical systems.

Once the components that make up the physical-digital learning environment have been described, the following

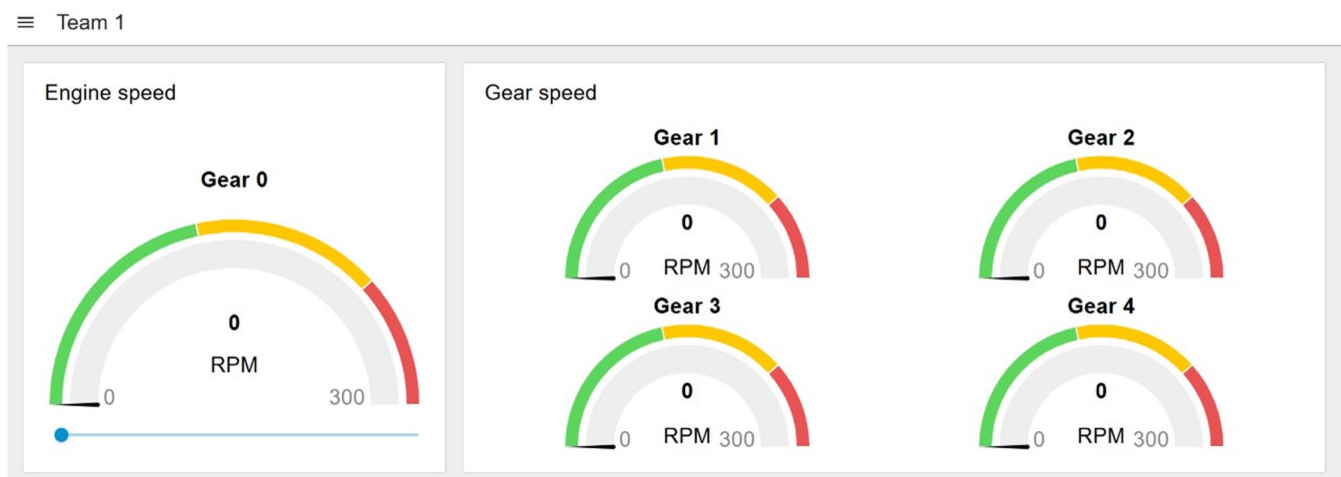


FIG. 5. Dashboard developed in Node-RED for real-time visualization of angular velocities.

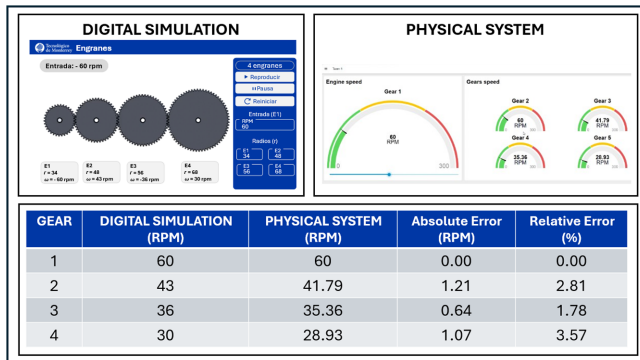


FIG. 7. Comparison between the digital simulation environment and the instrumented physical system.

section presents the methodology used to evaluate its implementation in an educational context. Specifically, it describes the type of study conducted, the characteristics of the participants, the design of the educational intervention, as well as the instruments used to measure its impact on student learning and perception.

B. Methodology

1. Study design and intervention overview

The study was conducted using a quasiexperimental design with a pretest and post-test, including a control group and an experimental group. The purpose of the intervention was to evaluate the impact of integrating the physical-IoT experimental system on first-year engineering students' engagement, technology acceptance, and conceptual understanding of rotational motion transmission systems. The general structure of the intervention is shown in Fig. 8.

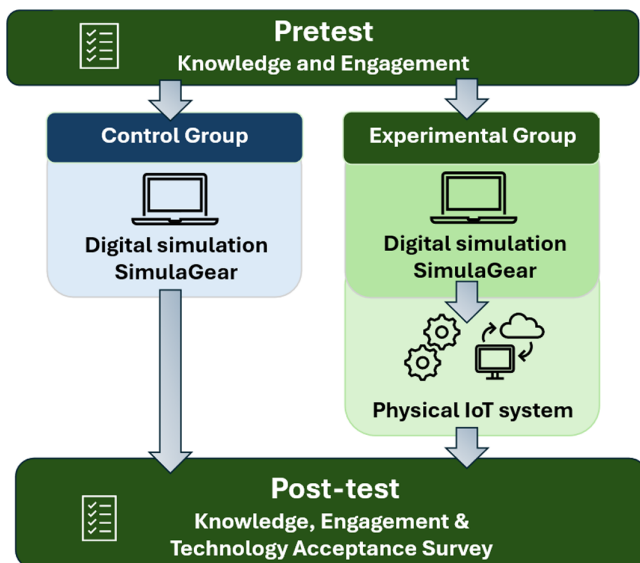


FIG. 8. General design of implemented educational intervention.

The learning activities focused on the analysis of motion transmission in gear systems, using pitch diameter as the main parameter to examine transmission ratios and the propagation of angular velocity throughout the system. Both groups worked with concepts related to circular motion, angular velocity transmission, rotation direction, and transmission ratios in gear arrangements. However, the groups differed in the type of technological environment used during the intervention.

The control group interacted exclusively with the SimulaGear digital simulation environment. During the session, students modified transmission configurations, analyzed changes in angular velocity, and made predictions about the behavior of rotational motion in different gear arrangements. The activity was oriented toward conceptual analysis and the interpretation of kinematic relationships, with the aim of encouraging students to explain system behavior beyond the mechanical application of procedures.

The experimental group participated in a hybrid physical-digital experience structured in two phases. In the first phase, students worked with the SimulaGear digital simulation, equivalent to the control group, in order to ensure a common conceptual exposure to the theoretical principles of rotational motion transmission. In the second phase, they worked with the physical-IoT experimental system, which integrated an instrumented physical gear system with real-time data visualization. During this stage, students explored different gear configurations, experimentally analyzed how angular velocity is transferred, and compared expected theoretical values with experimental measurements obtained through the instrumented system.

Unlike traditional laboratory practices mainly centered on procedural execution, the intervention was designed to promote the interpretation of experimental data, the comparison between theoretical and physical system behavior, the analysis of transmission ratios, and the conceptual understanding of how rotational motion is transmitted in gear systems.

To assess the effects of the intervention on students' learning experience and conceptual development, the following section describes the instruments used to measure engagement, technology acceptance, and conceptual understanding.

2. Impact assessment instruments

The three instruments used to assess the impact of the intervention are described in this section. These instruments were designed to measure students' conceptual understanding of rotational motion transmission systems, their level of engagement during the learning experience, and their acceptance of the technology integrated into the educational environment.

- **Conceptual understanding:** To evaluate students' conceptual understanding, a ten-item multiple-choice

questionnaire was designed, with each item including four options and only one correct answer. The instrument was intended to measure students' understanding of concepts related to four key topics related to circular motion and motion transmission in gear systems: (1) Relationship between angular and tangential velocity, (2) motion transmission in gear systems, (3) prediction of rotation direction, and (4) transmission ratios in multiple-gear systems. Scores range from 0 to 100 and are obtained by averaging the results of the ten items included in the assessment. The questionnaire was administered as both a pretest and a post-test to estimate knowledge level in conceptual performance before and after the educational intervention. The structure of the instrument and its validation through an individual expert judgment procedure are presented in the Appendix.

- **Engagement:** Student engagement was measured using the short student version of the Utrecht Work Engagement Scale for Students (UWES-S 9) [28]. This instrument conceptualizes engagement as a positive and persistent affective-cognitive state related to academic work, characterized by vigor, dedication, and absorption. The scale includes nine items distributed across three dimensions: vigor, which refers to students' energy, effort, and perseverance in course activities; dedication, which reflects students' sense of involvement, enthusiasm, and pride toward the course; and absorption, which describes students' concentration and enjoyment while engaging in course-related tasks. The overall engagement score was obtained by averaging the nine items, and dimension-specific scores were calculated by averaging the corresponding three items. The instrument has shown strong internal consistency, with a Cronbach's α of 0.93 for the full scale and reliability coefficients of 0.82 for vigor, 0.90 for dedication, and 0.84 for absorption [29].
- **Technology acceptance:** To evaluate technology acceptance of the learning environment used during the intervention, a questionnaire grounded in the technology acceptance model (TAM) was administered [24]. This model has been widely used in educational contexts to analyze the adoption of learning technologies. The instrument included five constructs: perceived enjoyment (PE), perceived ease of use (PEU), attitude toward use (ATU), intention to use (IU), and perceived usefulness (PU). The items were rated on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The purpose of the questionnaire was to compare technology acceptance between students who worked exclusively with the SimulaGear digital simulation and those who participated in a hybrid physical-digital learning experience that integrated the SimulaGear digital simulation, and the physical-IoT

TABLE I. Demographic characteristics of the participants.

	Control group $N = 18$	Experimental group $N = 19$	Total $N = 37$
Age (years)	18–19	18–19	18–19
Female N (%)	15 (83.3%)	4 (21.1%)	19 (51.4%)
Male N (%)	3 (16.7%)	15 (78.9%)	18 (48.6%)

experimental system. Reliability analyses reported in prior applications of the instrument showed Cronbach's α values ranging from 0.777 to 0.946, indicating satisfactory internal consistency [25].

3. Participants

The sample consisted of 37 first-year engineering students enrolled in introductory physics courses focused on fundamental mechanics concepts. Participants voluntarily joined the study after being invited by their instructors from two preexisting course sections. Assignment to the study conditions occurred at the course-section level rather than at the individual level; therefore, participants were not randomly assigned to the control and experimental conditions. Both sections consisted of first-year engineering students following the same common-core curriculum and had received comparable formal curricular preparation prior to the intervention. The control group included students from the bioengineering and chemical processes academic area, whereas the experimental group included students from the computing and information technologies area. The two sections differed substantially in gender composition, resulting in a higher proportion of female students in the control group and male students in the experimental group. Consequently, gender was not balanced across conditions. The participants were between 18 and 19 years old. The distribution of participants by group, age, and gender is presented in Table I.

This methodological approach allowed the study to examine the educational impact of integrating a physical-IoT experimental system into the learning process, in comparison with an exclusively simulation-based experience. By incorporating pretest and post-test measures of conceptual understanding and engagement, together with a postintervention technology acceptance instrument, the study sought to characterize changes in students' knowledge and learning experience, as well as their perceptions of the technological environment. The results derived from these measurements are presented and analyzed in the following section.

III. RESULTS

The results are presented according to the three outcome variables considered in the study: conceptual understanding, engagement, and technology acceptance. Thus, the effects of the intervention are examined in relation to

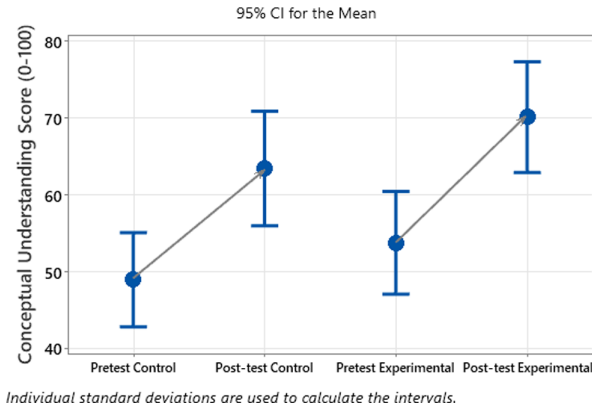


FIG. 9. Comparison of conceptual understanding scores between the control (SimulaGear) and experimental (physical-IoT) groups before and after the intervention. Points represent mean scores, and error bars indicate 95% confidence intervals.

students' learning, their involvement in the academic activity, and their perceptions of the technological environment used during the learning experience.

A. Conceptual understanding

The results for conceptual understanding show an increase in mean scores from pretest to post-test in both groups, as shown in Fig. 9. The control group improved from approximately 49 points in the pretest to 63 points in the post-test, while the experimental group increased from approximately 54 to 70 points. Although both groups showed progress, the experimental group achieved the highest post-test mean score. The overlap of the 95% confidence intervals suggests no clear visual evidence of large differences between groups at either measurement point.

Since the overall change in conceptual understanding was equivalent between the control and experimental groups, the learning gain was further analyzed by the four key topics included in the conceptual assessment. As shown in Table II, both groups showed a statistically significant improvement in motion transmission in gear systems, with positive mean differences in the control

group and the experimental group. In contrast, no significant changes were observed for the relationship between angular and tangential velocity or for the prediction of rotation direction in either group. A relevant difference was observed in the topic related to transmission ratios in multiple-gear systems: while the control group did not show a statistically significant gain, the experimental group presented a significant improvement.

These findings indicate a positive change in students' conceptual understanding of rotational motion transmission after the learning activities. Although the increase was similar in the control and experimental groups, the analysis by key topics provides a more detailed perspective on the learning gains. In particular, the physical-IoT intervention appears to have contributed more specifically to students' understanding of transmission ratios in more complex gear configurations, suggesting that the integration of physical experimentation with the digital environment may support the interpretation of motion transmission behavior in multigear systems.

B. Engagement

Engagement was analyzed through paired mean differences between the post-test and pretest scores for each dimension of the UWES-S scale: vigor, dedication, and absorption, as well as for the overall engagement score. The analysis tested whether students' engagement increased after the intervention.

For the control group (SimulaGear), the results showed no statistically significant differences between post-test and pretest scores in any of the engagement dimensions or in the overall engagement score, as shown in Table III.

Although positive mean differences were observed for vigor (4.35), absorption (2.69), and overall engagement (1.62), these changes were not statistically significant, with p values above 0.05. Dedication showed a negative mean difference (-2.19), suggesting a slight decrease from pretest to post-test; however, this difference was also not statistically significant ($p = 0.270$). These results indicate that the use of the digital simulation alone did not produce significant changes in students' engagement.

TABLE II. Difference of paired means by key topics. SimulaGear (control group). Physical-IoT (experimental group).

Null hypothesis: $Post\text{-}test\text{-}pretest = 0$				
Alternative hypothesis: $Post\text{-}test\text{-}pretest \neq 0$				
Key topic	Mean difference control group	p -value control group	Mean difference experimental group	p -value experimental group
1. Relationship between angular and tangential velocity	-0.0185	0.854	0.1228	0.202
2. Motion transmission in gear systems	0.333	0.000*	0.2281	0.000*
3. Prediction of rotation direction	0.1389	0.056	0.0526	0.331
4. Transmission ratios in multiple-gear systems	0.111	0.163	0.2368	0.016*

TABLE III. Difference of paired means in Engagement for SimulaGear group (control). *Note.* Statistical significance was assessed at a 95% confidence level ($p < 0.05$).

Null hypothesis: Post-test-pretest = 0			
Alternative hypothesis: Post-test-pretest > 0			
Dimension	Mean difference	<i>t</i> -value	<i>p</i> value
Vigor	4.35	1.67	0.114
Dedication	−2.19	−1.14	0.270
Absorption	2.69	1.10	0.288
Engagement	1.62	1.00	0.333

TABLE IV. Difference of paired means in engagement for physical-IoT group (experimental). *Note.* Statistical significance was assessed at a 95% confidence level ($p < 0.05$).

Null hypothesis: Post-test-Pretest = 0			
Alternative hypothesis: Post-test-pretest > 0			
Dimension	Mean difference	<i>t</i> value	<i>p</i> value
Vigor	4.31	2.50	0.025*
Dedication	2.42	1.83	0.088
Absorption	2.27	1.51	0.154
Engagement	3.00	2.58	0.022*

In contrast, the experimental group (physical-IoT) showed statistically significant improvements in specific engagement outcomes, as presented in Table IV. The dimension of vigor increased significantly from pretest to post-test ($M_{\text{diff}} = 4.31$, $t = 2.50$, $p = 0.025$), indicating that students reported higher levels of energy, persistence, and willingness to invest effort after participating in the physical-digital learning experience. In addition, the overall engagement scores also showed a statistically significant increase ($M_{\text{diff}} = 3.00$, $t = 2.58$, $p = 0.022$). Dedication showed a positive mean difference ($M_{\text{diff}} = 2.42$), with a marginal tendency toward improvement ($p = 0.088$), while absorption also increased ($M_{\text{diff}} = 2.27$), although this change was not statistically significant ($p = 0.154$).

The integration of the physical-IoT system with the SimulaGear digital simulation had a favorable effect on students' engagement, particularly in terms of vigor and overall engagement. Unlike the control group, where no significant changes were observed, the experimental group demonstrated measurable gains after the intervention.

C. Technology acceptance

The technology acceptance results for the SimulaGear digital platform, used by the control group, show generally positive student perceptions across all evaluated dimensions. As shown in Fig. 10, the median scores were above 4.0 on the Likert scale for all constructs, indicating

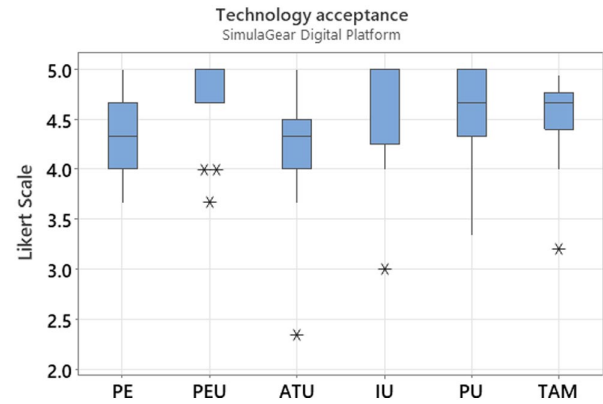


FIG. 10. Technology acceptance results for the SimulaGear digital platform in the control group. Likert scale: (5) Totally agree, (4) Agree, (3) Nor agree or disagree, (2) Disagree, (1) Totally disagree.

favorable levels of perceived enjoyment, perceived ease of use, attitude toward use, intention to use, perceived usefulness, and overall technology acceptance. The highest scores were observed for perceived ease of use, intention to use, perceived usefulness, and TAM, with several responses concentrated near the upper end of the scale. Although some lower outliers were identified, particularly in attitude toward use and intention to use, the overall distribution suggests that students perceived SimulaGear as an accessible and useful digital learning environment for supporting the study of rotational motion transmission.

Table V shows mean, median, boxes, whiskers, and outliers for the five dimensions and for TAM.

The technology acceptance results for the physical-IoT experimental system show highly favorable student perceptions across all evaluated dimensions. As shown in Fig. 11, the median scores for the physical-IoT experimental system were close to the upper end of the Likert scale across all TAM dimensions, including perceived enjoyment, perceived ease of use, attitude toward use, intention to use, perceived usefulness, and overall technology acceptance.

Compared with the control group results for the SimulaGear digital platform, the experimental group showed a more concentrated distribution of responses in

TABLE V. Boxplot data for technology acceptance. Control group, Fig. 10.

Variable	Mean	SD	Median	Box	Whiskers	Outliers
PE	4.31	0.46	4.33	4–4.67	3.67–5	0
PEU	4.71	0.42	5.00	4.67–5	4.67–5	3
ATU	4.18	0.59	4.33	4–4.5	3.67–5	1
IU	4.65	0.58	5.00	4.25–5	4–5	1
PU	4.63	0.48	4.67	4.34–5	3.34–5	0
TAM	4.49	0.42	4.67	4.4–4.77	4–4.93	1

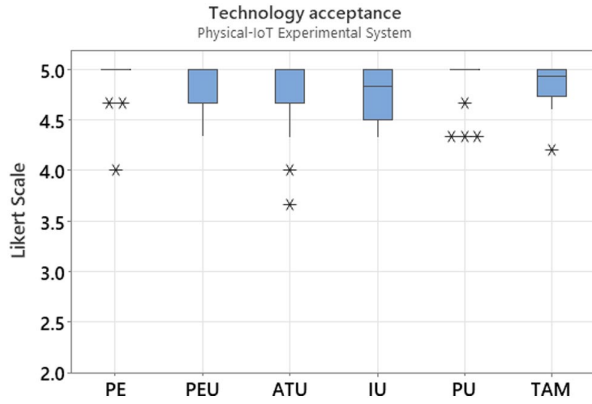


FIG. 11. Technology acceptance results for the physical-IoT experimental system in the experimental group. Likert scale: (5) Totally agree, (4) Agree, (3) Nor agree or disagree, (2) Disagree, (1) Totally disagree.

the upper range of the scale, particularly between 4.5 and 5.0. This pattern suggests that students perceived the physical-IoT system as highly useful, accessible, and engaging for supporting the learning of rotational motion transmission. Although a few lower outliers were observed, mainly in attitude toward use and overall TAM, the general distribution indicates strong acceptance of the physical-digital learning environment, with more favorable perceptions than those reported for digital-only experience. Table VI shows mean, median, boxes, whiskers, and outliers for the five dimensions and for TAM.

To determine whether the differences in technology acceptance between the experimental and control groups were statistically significant, an independent samples t test was conducted. The results showed that the experimental group reported a higher mean technology acceptance score ($M = 4.853$, $SD = 0.208$) than the control group ($M = 4.494$, $SD = 0.423$). This difference was statistically significant, $t = 3.17$, $p = 0.004$, with a mean difference of 0.359 and a 95% confidence interval ranging from 0.124 to 0.593. These findings indicate that students who interacted with the physical-IoT experimental system reported significantly higher technology acceptance than those who used only the SimulaGear digital platform.

TABLE VI. Boxplot data for technology acceptance. Experimental group, Fig. 11.

Variable	Mean	SD	Median	Box	Whiskers	Outliers
PE	4.91	0.24	5.00	5–5	5–5	3
PEU	4.84	0.28	5.00	4.67–5	4.33–5	0
ATU	4.74	0.38	5.00	4.67–5	4.33–5	2
IU	4.79	0.26	4.83	4.50–5	4.33–5	0
PU	4.88	0.25	5.00	5–5	5–5	4
TAM	4.85	0.21	4.93	4.73–5	4.66–5	1

IV. DISCUSSION

This study examined the educational impact of integrating a physical-IoT experimental system into a digital simulation-based learning environment for the study of rotational motion transmission in gear systems. The results provide evidence that both the digital-only experience and the physical-digital experience supported students' learning; however, the integration of the physical-IoT system produced more favorable outcomes in specific aspects of conceptual understanding, engagement, and technology acceptance.

Regarding conceptual understanding, both groups showed an increase from pretest to post-test. This finding suggests that the learning activities were useful for supporting students' understanding of circular motion and rotational motion transmission, regardless of the modality used. The improvement observed in the control group indicates that SimulaGear, as a digital simulation environment, can support the visualization and interpretation of kinematic relationships in gear systems. This result is consistent with prior research indicating that virtual laboratories and simulations can contribute to conceptual learning by allowing students to manipulate variables, visualize dynamic phenomena, and repeat learning scenarios under controlled conditions [19,20].

However, the analysis by key topics provides a more detailed interpretation of the learning gains. Both groups showed statistically significant improvement in the topic related to motion transmission in gear systems, suggesting that the digital simulation was sufficient to support basic understanding of how angular velocity is transferred between gears. In contrast, only the experimental group showed a statistically significant improvement in transmission ratios in multiple-gear systems. This distinction is important because multigear configurations require students to coordinate several relationships across the system, rather than analyzing only a single interaction between two gears. Therefore, the physical-IoT system appears to have contributed specifically to students' interpretation of more complex configurations, where theoretical prediction, physical behavior, and measured data must be connected.

This finding supports the idea that physical and virtual laboratories should not be understood as mutually exclusive alternatives, but as complementary learning environments. The digital simulation provides an idealized representation of the system, allowing students to explore controlled relationships among gear radius, angular velocity, and rotation direction. The physical system, in contrast, introduces students to the behavior of a real mechanism, including measurement, empirical variability, and the comparison between predicted and observed values. This is aligned with de Jong *et al.* [18], who argue that combining physical and virtual laboratories can strengthen science and engineering learning by taking advantage of the affordances of both environments. In the present study,

the integration of SimulaGear with the physical-IoT system created opportunities for students to move from model-based prediction to experimental validation, which is particularly relevant in engineering education.

The engagement results also suggest differences between the two modalities. In the control group, no statistically significant changes were observed in vigor, dedication, absorption, or overall engagement. Although students reported favorable acceptance of the digital simulation, the use of SimulaGear alone did not produce a measurable increase in engagement. In contrast, the experimental group showed statistically significant gains in vigor and overall engagement. This suggests that the physical-digital experience may have increased students' energy, persistence, and willingness to invest effort in the learning activity.

The increase in vigor is especially relevant because it reflects students' perceived energy and perseverance during academic work. The physical-IoT system required students to observe a real gear mechanism, interpret real-time angular velocity data, and compare experimental measurements with theoretical predictions. This type of activity may have promoted a more active and situated learning experience than the digital-only condition. Nevertheless, dedication and absorption did not reach statistical significance, although both dimensions showed positive mean differences in the experimental group. This result should be interpreted cautiously. It may indicate that the intervention had a clearer immediate effect on students' activation and effort than on deeper affective involvement or sustained immersion. Longer interventions, repeated experimental sessions, or more structured inquiry-based activities may be necessary to produce stronger effects across all engagement dimensions.

The technology acceptance results constitute one of the clearest findings of the study. Both groups reported high levels of technology acceptance, with favorable scores across the TAM constructs. This indicates that SimulaGear was perceived as useful, easy to use, and appropriate for supporting the learning of rotational motion transmission. However, the experimental group reported significantly higher overall technology acceptance than the control group. Students who worked with the physical-IoT system reported higher and more concentrated scores across the evaluated TAM dimensions, and the difference in overall technology acceptance between groups was statistically significant.

This result contributes directly to the research gap identified in the theoretical framework. Although TAM has been widely used to analyze educational technologies in higher education [24], fewer studies have examined how technology acceptance may change when a digital learning platform is integrated with a physical experimental system. Previous studies have used TAM to analyze emerging technologies such as augmented reality, virtual laboratories,

online environments, and digital shadow systems [25–27]. The present study extends this discussion by showing that students' acceptance of a digital modeling platform may increase when the platform is embedded within a physical-digital experience that allows students to compare simulation results with real-time experimental data.

From an instructional perspective, this finding suggests that technology acceptance is not determined only by the usability of the digital interface. Rather, it also depends on the pedagogical experience in which the technology is used. In this study, SimulaGear was accepted positively as a stand-alone simulation, but its integration with the physical-IoT system appears to have strengthened students' perception of usefulness, enjoyment, and relevance. The physical component may have helped students perceive the digital model as part of a broader engineering practice, in which theoretical predictions are contrasted with empirical measurements. This interpretation is consistent with the role of laboratories in engineering education, where students are expected not only to verify theoretical content but also to develop skills related to experimentation, data interpretation, system analysis, and understanding the limitations of real systems [14,15,17].

The higher engagement and technology acceptance observed in the physical-digital group should also be interpreted in light of a possible novelty effect associated with the physical-IoT system. Because students interacted with the instrumented physical system during a relatively short intervention, the initial interest generated by the hardware, real-time measurements, and interaction with a new technological environment may have contributed to their favorable perceptions. Previous research on emerging educational technologies has shown that first exposure to a novel technological environment can temporarily increase engagement, satisfaction, or perceived usability, making it difficult to separate the effects of novelty from those associated with the instructional design itself [30]. Longer-term implementations involving multiple sessions would help distinguish sustained effects of the physical-digital learning environment from responses partially associated with its initial novelty.

The results also have implications for the design of learning environments in introductory engineering courses. First-year students often face difficulties connecting abstract physical concepts, mathematical relationships, and real mechanical behavior. A physical-digital environment can support this connection by allowing students to work across multiple representations: mathematical relationships, digital simulation, physical mechanisms, and real-time data visualization. In the context of gear systems, this integration may help students understand that models are not only formulas to be applied but also tools for predicting, interpreting, and validating system behavior. This is consistent with the relevance of modeling in engineering education, where students need to represent

systems, analyze relationships among variables, and make informed decisions based on theoretical and empirical evidence [11–13].

Despite these contributions, the findings should be interpreted considering some limitations. First, the study was conducted with a relatively small sample of first-year engineering students, which limits the generalizability of the results. Second, the quasiexperimental design did not allow for random assignment of participants, and gender distribution was substantially unbalanced across the control and experimental groups. This imbalance should be acknowledged as a potential threat to internal validity, particularly because previous research in introductory physics has reported gender-related differences in some aspects of conceptual performance and participation in laboratory activities [31]. However, evidence from large-scale studies also indicates that gender differences in examination performance and final course grades in introductory physics, when present, tend to show small or weak effect sizes [32]. Therefore, the gender imbalance is considered a limitation of the study design that should be taken into account when interpreting between-group differences, without implying that the observed outcomes were attributable to gender. Third, the intervention was implemented over a short period, so the study does not provide evidence regarding the long-term retention of conceptual understanding or sustained engagement. Finally, although the conceptual instrument made it possible to identify learning gains by topic, the study did not include qualitative data such as interviews, written explanations, or observation protocols that could provide deeper insight into students' reasoning processes.

Future research should address these limitations by implementing the physical-digital environment with larger and more diverse samples, incorporating delayed post-tests, and using mixed-method approaches to analyze how students interpret the relationship between theoretical models, digital simulations, and physical measurements. It would also be valuable to explore whether similar physical-digital designs can be applied to other mechanical systems or engineering physics topics. In addition, future studies could examine how specific features of the physical-IoT system, such as real-time data visualization, sensor-based measurement, or physical manipulation of gears, contribute individually to engagement, technology acceptance, and conceptual understanding.

The findings suggest that the integration of a physical-IoT experimental system into a digital simulation environment can enrich the learning experience in engineering physics. The strongest evidence was observed in students' technology acceptance, followed by gains in vigor and overall engagement. In terms of conceptual understanding, the contribution of the physical-digital environment was more specific, appearing particularly in students' understanding of transmission ratios in multiple-gear systems.

Therefore, the value of the proposed environment lies not in replacing digital simulation with physical experimentation, but in articulating both resources to support model interpretation, experimental validation, and the connection between idealized and real-system behavior.

V. CONCLUSIONS

This study presented the design and evaluation of a physical-digital learning environment for the study of rotational motion transmission in introductory engineering education. The environment integrated the SimulaGear digital simulation with a physical-IoT experimental system composed of an instrumented gear mechanism, sensor-based data acquisition, wireless communication, and real-time data visualization.

The results show that both the digital-only and physical-digital learning experiences supported students' conceptual understanding. However, the physical-digital condition showed a specific advantage in the topic of transmission ratios in multiple-gear systems, suggesting that the integration of physical experimentation can support students when they need to interpret more complex mechanical configurations and compare theoretical predictions with experimental measurements. The findings also indicate that the physical-IoT experience had a favorable effect on students' engagement, particularly in vigor and overall engagement. In addition, technology acceptance was significantly higher in the physical-digital group than in the digital-only group. This suggests that students' acceptance of an educational technology depends not only on the digital tool itself, but also on the type of learning experience in which the tool is embedded.

The main contribution of this study is the development and educational evaluation of a learning environment that articulates digital modeling, physical experimentation, and real-time data visualization. This integration allowed students to connect idealized model predictions with empirical system behavior, supporting a more meaningful approach to learning rotational motion transmission in engineering physics.

Although the results are favorable, the study was limited by the small sample size, the quasiexperimental design, and the short duration of the intervention. Future research should involve larger samples, longer implementations, delayed post-tests, and qualitative analyses of students' reasoning processes. Overall, the findings support the value of integrating physical-IoT systems with digital simulations as a strategy for strengthening learning, engagement, and technology acceptance in introductory engineering education.

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DATA AVAILABILITY

There are no publicly available research data or software supporting this manuscript. Requests for further information or data should be sent to the authors.

APPENDIX

This appendix provides supplementary methodological details on the design and content validation of the conceptual understanding test used in this study. It describes the instrument's structure, the expert judgment procedure, and the results of the content validity assessment.

1. Design and validation of the circular motion and gear concepts test

To evaluate the learning gain associated with the didactic activity, a conceptual questionnaire consisting

of ten multiple-choice items was designed, with four answer options, only one of which was correct. The instrument aims to measure students' understanding of concepts related to circular motion, in particular: (1) Relationship between angular and tangential velocity, (2) motion transmission in two-gear systems, (3) prediction of rotation direction in three-gear systems, and (4) transmission ratios in multiple-gear systems. The questionnaire was designed to be administered as a pretest and post-test to first-year engineering students, in order to estimate changes in conceptual performance before and after the educational intervention.

The structure of the instrument was organized into four conceptual dimensions (Table VII). Items 1, 2, and 3 evaluate concepts related to the relationship between angular and tangential velocity; items 4, 5, and 6 focus on motion transmission in two-gear systems; items 7 and 8 address prediction of rotation direction in three-gear systems; and items 9 and 10 evaluate transfer and prediction in a four-gear system. The content of the items includes graphical representations of gear systems and questions aimed at the conceptual and predictive interpretation of the system's behavior.

TABLE VII. Conceptual dimensions of the instrument.

Conceptual dimension	Items	Concepts assessed	Sample item
1. Relationship between angular and tangential velocity	1, 2, 3	Relationship among radius, angular velocity, and tangential velocity in a rotating rigid body.	Item 1. A point on the edge of a gear rotates with constant angular velocity ω . If the radius of the disk is doubled and ω remains constant, the tangential velocity of the point on the edge: A) Remains the same, B) Is reduced by half, C) Doubles, D) Quadruples.
2. Motion transmission in two-gear systems	4, 5, 6	Equality of tangential velocities at the point of contact, change in angular velocity due to differences in radii, and prediction of the direction of rotation.	Item 4. Two gears are in contact without slipping. At the point of contact between the two gears: A) The angular velocities are equal, B) The tangential velocities are equal, C) The directions of rotation are the same, D) The angular momentum is equal.
3. Prediction of rotation direction in three-gear systems	7, 8	Effect of the intermediate gear on the direction of rotation and on the overall angular velocity ratio between the first and last gears.	Item 8. In a system of three aligned gears, the intermediate gear: A) Changes the overall angular velocity ratio between gear 1 and gear 3, B) Does not affect the overall angular velocity ratio between gear 1 and gear 3, C) Doubles the final angular velocity, D) Reduces the final angular velocity by half.
4. Transmission ratios in multiple-gear systems	9, 10	Prediction of the direction of rotation and determination of the relationship between angular velocities based on the radii of the gears.	Item 9. In a system of four aligned gears, if gear 1 rotates clockwise, gear 4 rotates: A) Clockwise, B) Counterclockwise, C) Does not rotate, D) Depending on the radii.

TABLE VIII. Percentage of favorable agreement and decision by item.

Item	Clarity of wording	Internal coherence	Absence of response induction	Appropriate language	Measures what it intends to measure	Overall average	Methodological decision
1	100%	100%	100%	100%	100%	100%	Retained
2	83.3%	100%	100%	100%	100%	96.7%	Retained
3	100%	100%	83.3%	100%	100%	96.7%	Retained
4	83.3%	100%	100%	100%	100%	96.7%	Retained
5	100%	100%	100%	100%	100%	100%	Retained
6	100%	100%	83.3%	100%	100%	96.7%	Retained
7	100%	100%	100%	100%	100%	100%	Retained
8	83.3%	100%	100%	100%	100%	96.7%	Retained
9	100%	100%	66.7%	100%	100%	93.3%	Retained, subject to review for potential response induction.
10	100%	100%	100%	100%	100%	100%	Retained

2. Content validity analysis through expert judgment

The content validity of the instrument was evaluated using the individual aggregates method [33]. Six Ph.D.-level experts, identified as A, B, C, D, E, and F, independently evaluated the ten questionnaire items. The experts were physicists or engineers from four universities, all of whom were faculty members in science or engineering departments and had between 10 and 20 years of teaching experience. For each item, five constructs were considered: clarity of wording, internal coherence, absence of response induction or bias, appropriateness of the language for the respondent's level, and correspondence with the intended construct to be measured. Responses were coded dichotomously, assigning 1 to a favorable evaluation and 0 to an unfavorable evaluation. For the criterion related to response induction, the coding was applied equivalently so that a value of 1 indicated absence of bias and a value of 0 indicated the presence of potential bias.

For each construct, the percentage of favorable agreement among experts was calculated. The results show a highly favorable evaluation of the instrument (Table VIII). For the constructs of internal coherence, appropriate language, and measurement of the intended construct, all items obtained 100% favorable agreement. For clarity of wording, items 2, 4, and 8 obtained 83.3% favorable agreement, while the remaining items reached 100%. For the construct related to the absence of response induction

or bias, items 3 and 6 obtained 83.3% favorable agreement, and item 9 obtained 66.7%, indicating that this was the criterion with the lowest level of agreement among experts.

According to these results, items 1, 5, 7, and 10 reached 100% favorable agreement across all criteria and were therefore directly accepted. Items 2, 3, 4, 6, and 8 obtained an overall average of 96.7%, with partial agreement only in one specific criterion; therefore, they were considered appropriate for the instrument. Item 9 obtained an overall average of 93.3%; however, it showed 66.7% favorable agreement in the criterion related to the absence of response induction, so it was reviewed and adjusted before application.

Table IX presents the results of the analysis by construct, which makes it possible to identify that the instrument shows an adequate correspondence between the items and the content intended to be assessed. All items were considered coherent, appropriate for the level of the target population, and relevant for measuring the intended constructs.

Finally, the six experts showed favorable agreement on the three general aspects evaluated (Table X). The items support the achievement of the research objective, are logically and sequentially organized, and the number of items is sufficient to collect the necessary information.

This result supports the overall relevance of the instrument as a conceptual questionnaire for measuring learning

TABLE IX. Results of the analysis by construct.

Evaluated criterion	General result
Clarity of wording	High overall rating; three items obtained 83.3% favorable agreement.
Internal coherence	100% favorable agreement across the 10 items.
Absence of response induction	Overall favorable rating; item 9 required review.
Appropriate language	100% favorable agreement across the 10 items.
Measures of what it intends to measure	100% favorable agreement across the 10 items.

TABLE X. Percentage of favorable agreement on general aspects.

General aspect	Favorable agreement
The items support the achievement of the research objective	100%
The items are logically and sequentially organized	100%
The number of items is sufficient to collect the information	100%

gain in topics related to circular motion and motion transmission in gear systems.

Based on the judgment of the six experts, the instrument presents favorable evidence of content validity. The ten items obtained overall favorable agreement percentages equal to or greater than 93.3%, and all were positively rated in the criteria of internal coherence, appropriate language, and correspondence with the intended construct

to be measured. According to the individual aggregates procedure described by Corral [33], items with partial agreement do not require immediate elimination, but rather review, reformulation, or substitution when necessary. Therefore, it was decided to retain the ten items, making minor adjustments to those with partial agreement, particularly item 9, due to its lower agreement percentage in the criterion related to the absence of response induction.

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