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Original research article

Development of a didactic solution for teaching concepts related to Digital Twins using Educational Robot

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ABSTRACT

Engineering education faces ongoing challenges in keeping pace with the technological demands driven by the need to apply Industry 4.0 concepts in student training. In response to this, the present study introduces the development of a pedagogical tool built around an educational robot produced through 3D printing. The aim is to integrate active learning methodologies with key Industry 4.0 technologies, such as Digital Twins, asset administration shells, and computational simulation, to create a practical and dynamic learning environment. This hands-on approach was implemented in a graduate-level course on Advanced manufacturing engineering, specifically in the Process simulation module. The activity involved the use of the robot alongside a real-time, bidirectional computational model capable of reading and writing data, applying the Digital Twin concept. The study followed a mixed-method action research design. Results from a student feedback survey revealed that 100% of participants agreed the experience with the computational robot helped solidify theoretical concepts. Furthermore, 77.3% gave the learning experience the highest possible rating, and 95.5% recognized the robot's potential for use in other modules and courses. These findings suggest that this approach offers an effective strategy for engineering education that is aligned with the principles of Industry 4.0.

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1. Introduction

The rapid evolution of digital industrial technologies demands that production, training, and education systems adapt accordingly [1]. As digitalization reshapes manufacturing, there is a growing need for workers and engineers proficient in information and communication technology. In response, learning factories have emerged, integrating innovative methods to enhance skill development [2]. While higher education institutions are key to supporting Industry 4.0 transitions, many were established in earlier industrial eras and lack alignment with current digital skill needs [3]. Industry 4.0 emphasizes both hard (technical) and soft (non-technical) skills, highlighting a critical area for ongoing research and educational reform [4].

Engineering education in Brazil remains predominantly traditional, making it difficult to keep pace with the rapid technological changes brought by Industry 4.0 [5]-[7]. Although higher education institutions

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have begun incorporating active learning methodologies to modernize curricula and promote student engagement, these efforts are still emerging and often lack integration with cutting-edge digital technologies. Education 4.0, a concept aligning educational practices with the demands of Industry 4.0, calls for the adoption of innovative teaching models that equip students with both technical and soft skills necessary for a digitalized industrial landscape [8]-[11]. One promising approach is the learning factory model, which bridges the gap between theory and practice by simulating real-world industrial environments [12], [13]. Learning factories are well-established in developed countries, particularly across Europe, but remain scarce in Brazil [14], [15]. This limits opportunities for Brazilian engineering students to gain hands-on experience with technologies central to Industry 4.0, such as Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, Digital Twins (DT), and advanced robotics [10]. Among these technologies, DT offer significant potential to enhance active learning by providing realistic, interactive, and virtual environments that mirror complex industrial systems. However, the intersection of digital twin technology, active learning methodologies, and Industry 4.0 skill development has not been thoroughly investigated [16]. This underlines a notable research gap: the need for integrated educational frameworks that effectively combine active learning with emerging technologies to prepare students for the evolving demands of the industrial sector. Addressing this gap is essential for aligning Brazilian engineering education with global trends and workforce expectations.

This study presents the development and implementation of a 3D-printed educational robot designed to teach Industry 4.0 technologies, with a focus on digital twinning skills. Aimed at providing a replicable model for engineering education, the robot features configurable components to support diverse hands-on learning activities and integrate theory with practice. The research employs a qualitative action research methodology to examine how the robot supports active learning and skill development. Core topics include DT, Asset Administration Shells (AAS), and Computational Simulation. The study addresses the research question: *"Does the application of the educational robot support student engagement and the development of Industry 4.0-related technical skills?"* Findings, based on student feedback, highlight the robot's potential to enhance engagement and foster relevant technical competencies in engineering education.

2. Literature Review

Industry 4.0 brings many important concepts to its applications and understanding them is essential for more effective applications. Regarding the connection between the physical and virtual environments, Industry 4.0 encompasses essential concepts such as the definition of an asset, its asset management shell, modeling, simulation, and digital twin. This review summarizes these essential technical concepts (e.g., AAS; modeling, simulation, and digital twin) and then discusses contemporary pedagogical approaches for teaching them in engineering courses, with an emphasis on learning factories and digital twin teaching experiences. Both topics are directly interconnected, as AAS is the digitization of an asset, which in turn can be accessed through a simulation model that, by communicating in real time, receives and sends information, achieving what is defined in the literature as a digital twin. The concepts of AAS/OPC UA, discrete-event simulation, and digital twin were intentionally taught in a learning factory environment with project-based learning. Recent reviews indicate that learning factories create authentic tasks in which interoperability (AAS/OPC UA) and modeling/validation (simulation/DT) are integrated, favoring engagement and transfer to real-world contexts [17]. In particular, 2024/2025 syntheses show that DT activities in engineering courses are more effective when they involve a physical asset and integration of shop floor data into the digital model, exactly the role of AAS/OPC UA in the proposal of this study [18].

2.1 Asset Administration Shell

The increasing digitalization of industrial processes requires solutions that ensure interoperability and efficient asset management. In this context, the AAS emerges as a core concept within Industry 4.0, providing a standardized digital representation of an asset. According to IEC 63278-1 [19], the AAS offers uniform access to information and services, facilitating interaction between software applications both within and across organizational boundaries. The AAS is defined as a digital interface that captures and organizes essential data related to an asset, including its intrinsic properties, operational parameters, and technical functionalities [20]. This structure supports secure and standardized interactions by enabling communication across different AAS clusters. As described by Coda [21], the AAS is composed of sub models where all asset-related information and functionalities are described, including its characteristics, properties, status, parameters, measurement data, and capabilities. This approach allows the use of various communication channels, ensuring the connection between the physical and digital worlds. Interaction with the AAS can take different forms depending on the technical requirements involved. According to Ye et al. [20], the Platform Industrie 4.0 recognizes three primary AAS types:

- Passive: Functions as a static file or a package of files, storing standardized information (e.g., XML or JSON) for transmission between value chain partners.
- Reactive: Enables dynamic interactions via client-server communication, allowing real-time data queries and updates.
- Proactive: Operates in a peer-to-peer communication environment, enabling the AAS to act autonomously in decision-making and optimization within connected industrial systems.

Thus, the AAS plays a fundamental role in implementing Industry 4.0 by promoting the integration of physical assets with digital systems through a standardized and interoperable architecture. Its use facilitates process automation and real-time data analysis. Additionally, AAS can be implemented alongside the Reference Architectural Model for Industry 4.0 (RAMI 4.0), a three-dimensional framework designed to support the understanding of standards, models, and the development of digital manufacturing. RAMI 4.0 aims to enable the connectivity of industrial systems by integrating key elements of Industry 4.0 into a cohesive structure [22].

2.2 Modeling, Simulation and Digital Twins

According to the Brazilian Association of Production Engineering (ABEPRO) [23], Production Engineering is divided into ten knowledge areas, each comprising multiple subdivisions. Among them is the subfield of Operations Research, which ABEPRO defines as:

> "The resolution of real-world problems involving decision-making through mathematical models, usually processed computationally. It applies concepts and methods from other scientific disciplines in the design, planning, and operation of systems to achieve their objectives. It aims to introduce objectivity and rationality into decision-making processes while accounting for the subjective and organizational context that characterizes such problems." (ABEPRO [23])

Within this area lies the subfield of Modeling, Simulation, and Optimization, which focuses on using computational simulation to optimize production processes. The integration of simulation with Industry 4.0 technologies such as the IoT and big data is driving the advancement of smart manufacturing. Data collected from sensors and actuators enables real-time adjustments, allowing large-scale customization and resource optimization. This approach enhances efficiency while minimizing waste and improving the utilization of materials and energy. Consequently, simulation supports both industrial performance and the adoption of sustainable practices [24], [25]. Monteiro et al. [26] highlighted that digital simulation within Industry 4.0 transforms production processes by integrating physical and digital realms, offering strategic, efficient, and sustainable solutions to the challenges of modern manufacturing. The real-time connection between physical and virtual environments defines the concept of the DT. According to Kritzinger et al. [27], DT applications can be categorized into three subtypes (i.e., Digital Model, Digital Shadow and Digital Twin), based on the level of integration between physical assets and their digital counterparts, as shown in Figure 1. These classifications differ in terms of the degree of bidirectional data flow between the physical system and its digital representation.

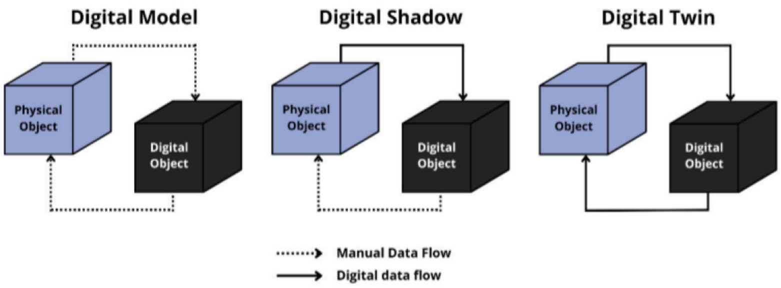

Figure 1. Subcategories of Digital Twin Applications (Source: Adapted from Kritzinger et al., [27])

A literature review conducted by Linder et al. [28] revealed that nearly all definitions or descriptions of DT emphasize the communication between a real physical asset or entity and a virtual representation. This data exchange must occur in real time and follow standardized protocols to ensure consistency across components, data sources, and services. Campos [16] presented the DT as a virtual learning factory, offering students a learning environment aligned with contemporary industrial demands. The term learning factory refers to physical or virtual environments that focus on training students or employees through hands-on problem-solving activities derived from real-world factory operations. These learning factories allow for experimentation and testing of procedures with the support of involved stakeholders [29]. According to Castro [30], the application of DT technologies has been steadily increasing across various sectors, including smart cities, manufacturing, and healthcare, among others.

2.3 Education in Production Engineering

The ABEPRO [23] defined Education in Production Engineering as a field that encompasses the management of educational systems at all levels and in all aspects. This includes everything from the training of personnel, such as faculty and administrative staff, to the organization of the didactic-pedagogical structure, with particular emphasis on the course's pedagogical project. Teaching methodologies and learning tools are also central elements of this area. Given its characteristics, Education in Production Engineering can be considered a form of "Pedagogical Engineering." Its main goal is to consolidate these elements and offer viable alternatives for course organization aimed at enhancing teaching practices. After all, professors are already deeply engaged in this area, but they often lack the necessary support to delve further into reflection and research [23]. ABEPRO breaks this field down into five interconnected subareas: the study of production engineers' training, the development and application of research and extension in Production Engineering, the study of ethics and professional practice in the field, pedagogical practices and the assessment of the teaching-learning process, and the management and evaluation of educational systems within Production Engineering programs [23]. Although there is a specific area in Production Engineering focused on engineering education, training engineers is increasingly challenging as it must keep pace with a rapidly changing world. The traditional lecture-based and passive learning model has proven to be less effective in preparing future engineers to solve complex, multidisciplinary problems. In this context, active learning methodologies have emerged as innovative and effective approaches, gaining traction in engineering education [30].

Nota et al. [31] pointed out that the use of technology through active learning methodologies supports student learning and improves engagement. The authors further highlight simulation as an opportunity to bridge the gap between theory and practice, enhancing students' understanding of the content. The current engineering environment demands for an increasing level of interdisciplinarity, innovation, creativity and cross-domain thinking as well as the consideration of sustainability aspects. New concepts, such as DT and complex product systems lead to the need for integrated product development approaches and new methods that put the user perspective in focus. This also needs to be an integral part in today's teaching concepts of the next generation of engineers [32].

From the Production Engineering perspective, recent international curricula emphasize competencies in manufacturing systems, digital integration, data-driven decision-making, and process design [33], [15]. Reports on curriculum reviews and integrative manufacturing modules show the incorporation of practical projects, prototyping, and connections to industrial systems (e.g., OPC UA) to align learning with industry needs [34], [35]. The learning factory proposed here operationalizes these guidelines by offering a scaled-down value chain (physical asset ↔ AAS/OPC UA ↔ simulation/DT) that allows graduate students to practice flow modeling, interoperability, and validation, core competencies for Production Engineering 4.0. [36].

3. Materials and Methods

This study adopted a qualitative-quantitative approach, employing the action research method, as it describes the development and implementation of a learning factory as a pedagogical tool in a graduate program in Advanced Manufacturing Engineering. The research employed a mixed-methods approach, which allowed for a more complete understanding of the phenomenon under study [37]. The qualitative component consisted of both formal and informal observations of student activities, as well as the open-ended responses from the questionnaire. The quantitative component was the analysis of the numerical data from the survey (the Likert scale). The combination of these two approaches provided a holistic view: the quantitative data showed the magnitude of the change in students' perceptions, while the qualitative data offered a contextual understanding of why this change occurred. Tripp [38] discussesed the concept of action research in an educational context, defining educational action research as a strategy for the development of teachers and researchers, enabling them to use their research to enhance their teaching and, consequently, student learning. In terms of its nature, this is an applied research project characterized by its practical focus, aiming to generate results that can be immediately applied to solve real-world problems [39].

The research was carried out at the Amazonas State University in partnership with a company in the industrial sector, supported by Research, Development and Innovation (RD&I) funds from the Manaus Industrial Estate's Information Technology Law. The main objective is to describe the application of a 3D-printed educational robot as a teaching tool for Industry 4.0 technologies (learning factory), particularly regarding digital twinning skill, providing a replicable model for other engineering educational institutions. A Learning Factory is a realistic production environment that simulates industrial processes for educational, training, and research purposes, especially in manufacturing and Industry 4.0. The goal is to provide a hands-on, action-oriented experience where students learn through direct interaction with systems and technologies, developing skills in a context that resembles the real world [15].

An explanatory mixed methods design with sequential data collection was employed: (i) observational data during the laboratory sessions and (ii) a post-activity survey. The observations were non-participatory, with records consisting of field notes (time, event, evidence) and an operational checklist (server connection, writing tests, model validation). A Likert-scale questionnaire (1–5) was then administered to measure conceptual understanding, engagement, and perceived usefulness. Survey responses were summarized using means and percentages. The survey instrument was reviewed by subject-matter experts (content validity) and piloted with adjustments for clarity. The specific goals are to: a) describe the infrastructure needed to implement the educational robot, including the lab setup, software, and equipment; b) show how didactic activities are planned and carried out, emphasizing student interaction with the robot and the related pedagogical goals; and c) assess how the robot contributes to student learning, emphasizing engagement, technical skill development, and problem-solving abilities.

3.1 Unit Analysis and Overview

The unit of analysis in this study is an educational product developed as part of the research and innovation project, incorporating software, hardware, and a virtual product designed through computer simulation. This product constitutes a hands-on learning environment, equipped with an educational robot and simulation software, replicating an industrial production setting.

3.1.1 Collaborating Team

The undergraduate students were responsible for the physical construction of the robots, including 3D printing of parts, assembly of electronic components, and software development focused on creating the robot's AAS. This team consisted of undergraduates in electrical/electronic engineering and automation. The master's students supported and advanced the development of the AAS, modeled the robot's digital twin through computer simulation, and carried out system-wide tests to validate the integrated solution. The master's students on this team are pursuing a master's in production engineering from the Federal University of Amazonas and a master's in electrical engineering from the State University of Amazonas. The faculty members provided research guidance, defined pedagogical goals, and facilitated the implementation of the educational product in the classroom, ensuring the project's alignment with educational objectives. The teacher responsible for the classroom application was Professor Dr. Ely Sena de Almeida, who is a professor at the Federal University of Amazonas and taught the "Simulation of Automated Production Systems" module in the Postgraduate program at the State University of Amazonas.

3.1.2 The Educational Product

The chosen approach to implement Industry 4.0 concepts and technologies was to use an educational robot built using 3D printing. This decision was based on the availability of 3D printers for robot production, the flexibility for customization and integration of additional components, and the ability to manufacture a larger number of robots to serve the entire class. All of this ensures that its construction enables the application of important Industry 4.0 concepts in an accessible, effective, and replicable manner across other academic institutions.

The innovation of this study does not lie in building a learning factory with cutting-edge technologies, but rather in merging well-established pedagogical principles with a low-cost technological platform. While other learning factories, such as Purdue University's, rely on state-of-the-art manufacturing equipment and high-cost commercial robots [40], the proposed model shows that it is possible to achieve equally meaningful and comparable learning outcomes with limited resources.

Unlike educational solutions that use only simulation or virtual environments detached from the factory floor [41], this proposal integrates a low-cost, real physical asset with an Asset Administration Shell (AAS), as per IEC 63278-1 [42]. This setup exposes services and data via OPC UA [43] and closes the loop with discrete-event simulation to compose a functional DT. Recent reviews highlight a gap in standardized interoperability and end-to-end validation within didactic experiences using DTs [36]. Case studies demonstrate the role of OPC UA in this realization [35], but it is rarely associated with the standardized AAS in a complete pedagogical exercise. Thus, our learning factory provides a replicable pipeline (physical asset → AAS → OPC UA → simulation/DT) that materializes Production Engineering 4.0 competencies in a single lesson plan. In total, ten robots were made available for the graduate course, with students organized into teams of two or three, allowing for hands-on application of the concepts learned. The robot used is a community-developed robotic arm, part of an open-source collaboration project led by an online community of students and developers. The original design was based on the project by Florin Tobler (Figure 2) and underwent several rounds of open hardware and software modifications.

The implementation of these robots and the infrastructure required for classroom activities involved a range of resources, including 3D printers for manufacturing parts, computers and servers for data processing, as well as appropriate tables and workbenches for the classroom environment. The ten robots developed were placed in a laboratory at the Amazonas State University, which already had computers and software for computer simulation. This environment was used for practical classes focusing on the application of concepts related to Industry 4.0 and the integration of advanced technologies, especially about computer simulation and digital twins. The configuration of the laboratory allowed the students to interact directly with the robots and simulation tools, promoting the practical application of the theoretical knowledge acquired during the classes.

3.1.3 Graduate Module on Process Simulation

The graduate course that utilized the developed learning factory structure was the result of a partnership between an industry within the Manaus Industrial Hub and the University of the State of Amazonas. It is a Lato Sensu postgraduate program in Advanced Manufacturing Engineering, with the specific module related to this project being "Simulation of Automated Production Systems," taught by Professor Dr. Ely Sena de Almeida. The process simulation module served as the context for implementing the educational product. In this module, students had the opportunity to apply theoretical concepts in a practical setting, using both the educational robot and simulation software. The primary concept addressed in the course was the use of computer simulation to create a DT. Additionally, and no less importantly, the concept of the AAS and its real-time communication between the physical and virtual environments was explored.

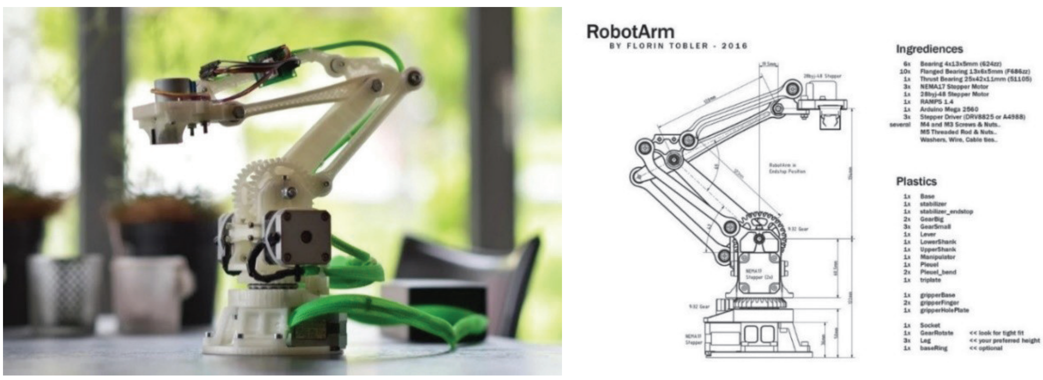

Figure 2. Robotic Arm developed by Florin Tobler [44]

4. The Proposed didatic solution

4.1 Pedagogical Approach

The educational proposal was designed in two complementary phases. In the first phase, undergraduate and master's students participated in the creation of the learning factory: they developed the educational robot, printed the parts, programmed the firmware, structured the robot's AAS, and validated its basic interoperability. This phase was a technical-educational project, the final product of which was the ready-to-use educational infrastructure. In the second phase, the focus of this study, the learning factory was used in a graduate course to apply the concepts of simulation and digital twin. The graduate students were challenged to integrate the physical robot via AAS/OPC UA into the simulation environment (FlexSim), building the functional digital twin and validating it in the classroom. This phase followed a project-based learning pedagogical approach in a learning factory context: students were exposed to an authentic problem (how to represent and control a physical asset through DT), worked collaboratively on the solution, and reflected on the challenges and results. The professor acted as a tutor, guiding the progression of the activities and fostering critical discussions.

The choice of this pedagogical approach is based on three main reasons. First, the use of active methodologies, such as project-based learning in a learning factory environment, is recognized for increasing engagement, conceptual retention, and the ability to apply knowledge in real-world situations, all of which are critical aspects of Industry 4.0 training. Second, the two-stage division (undergraduate/master's degree in construction and graduate degree in application) allowed the level of complexity to be tailored to the competencies of each audience: for undergraduate and master's students, the hands-on learning experience in developing the robot, the AAS, and the construction of this learning factory; for graduate students, the more advanced challenge of integrating and using the digital twin in simulation. Third, the choice of using a real physical artifact (educational robot) integrated with digital models sought to create an authentic engineering situation, where students would face the same challenges encountered in industrial projects, interoperability, systems integration, and performance validation. In this way, the adopted method not only taught concepts, but also promoted transversal skills such as collaboration, problem-solving and systemic thinking.

4.2 Development and application in the classroom

The development of the practical activity can be categorized into three areas: Hardware, Software, and Computational Simulation. The hardware area refers to the entire development and construction of the robot, starting with the creation of parts using a 3D printer and assembling the complete structure of the robotic arm. The software area refers to the development of each robot's AAS, and the simulation area refers to the creation of a digital twin. These three aspects, combined, enable students to visualize these concepts and validate the creation of their digital twin in a practical and efficient way through the communication of the simulation model they developed, which communicates with the AAS and can then control the physical object by sending commands. All three main components of this system can be understood, visualized, and validated by the student through the practical class with their use. The construction strategy for the proposed didactic solution began with the validation of a robot prototype that included all the desired main components, such as hardware, software (AAS), and simulation. Once validated, the production of the remaining nine robots began. The assembly process is shown in Figure 3.

Figure 3. Evidence of the Robot Manufacturing Stage (a) Raspberry Assembly (b) Robot Parts (c) Assembled Robots (Source: Authors own work)

Regarding the software area, activities such as firmware adjustments were carried out, specifically the programming of the robot using open-source code available online [45] which was embedded into the Raspberry Pi. However, the focus was the development of the AAS for the robot. The developed AAS is reactive in nature and allows dynamic interactions through real-time client-server communication. The creation of the robot's AAS followed the layer structure defined by RAMI 4.0: Asset, Integration, Communication, Information, Functional, and Business. Each layer is handled by a specific component: the physical robot corresponds to the Asset layer; integration is handled by the Raspberry Pi; the communication layer uses OPC UA and MQTT protocols; the information layer is implemented through AASX (AASX Server is an application that hosts and serves AAS packages); the functional layer is implemented in Python; and the business layer is intended for future development, as illustrated in Figure 4.

Within the software architecture, the AAS acts as the central entity responsible for providing an API via an OPC UA server. Additionally, the AAS logs variable data into a database that communicates directly with the asset via the integration layer. This architecture is shown in Figure 5. It is important to highlight that the computational model created in the postgraduate classroom fits within this architecture as a client. It accesses the AAS data to read or write variables and thus controls the physical environment. The AAS includes an integration layer that communicates with the robot hardware, and the robot itself has its own integration layer. Both systems exchange information using the MQTT protocol, which employs a publish/subscribe (pub/sub) messaging architecture.

As for the structure of the AAS, it is composed of two main sub models: the Nameplate, which holds detailed information about the product and its manufacturing, and the Pick and Place, which is used to

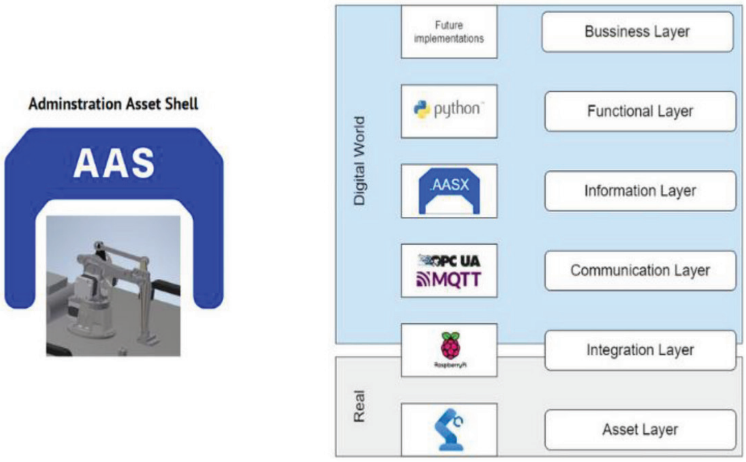

Figure 4. AAS and Implemented RAMI 4.0 Layers (Source: Authors own work)

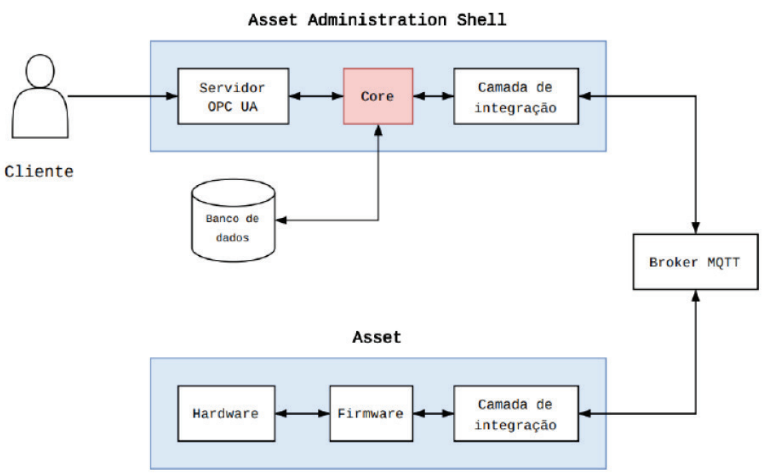

Figure 5. Software Architecture of the Educational Robot (Source: Authors, 2025)

control and monitor the robot's manipulation activities. The Pick and Place control the start of each routine and monitors the robot's operational state. Figure 6 presents the structure of the AAS, with the right side showing the variables via the AASX interface.

The instance used in the classroom practice is "PickAndPlacePositioning: SCM". This instance is primarily responsible for controlling and monitoring the Pick and Place routine, containing both the control sub model and the monitoring sub model of the robot's current position. Simply put, Pick and Place refers to the movement of apart from point A to point B, as shown in Figure X. The robot's pick and place routine is executed by changing 7 variables: 3 for Pick (X, Y, Z), 3 for Place (X, Y, Z), and the OperationalState variable, as shown in Figure 7.

As mentioned, the robot executes the Pick and Place routine, where the pick has three millimeter-based values representing Cartesian coordinates, and the same applies for the place values. The OperationalState variable can take on values such as Start, Error, Idle, and Calibrate. When set to Start, the robot begins the routine using the stored pick and place values.

With the hardware and software development complete, we can now discuss the computational simulation and digital twin model built by the students in the classroom. The simulation software used was FlexSim® version 2022.2, and the communication protocol was OPC UA. Communication with the physical robot occurs through the robot's AAS. FlexSim communicates with the AAS, which in turn sends and receives data from the physical environment via the previously explained architecture. Within this setup, various types of DT can be created based on the available AAS variables and the developer's goals.

For classroom use, the proposed Computational Model simulates the arrival of parts via conveyor belts. When a part reaches the end of the line, FlexSim sends the pick and place positions and the operational state to the robot to execute its routine. The model must first check the robot's availability by reading the OperationalState variable. Once availability is confirmed, the process is executed as shown in the flowchart in Figure 8.

The proposed classroom computational model is shown in Figure 9. It is important to emphasize that this model was developed based on simulation

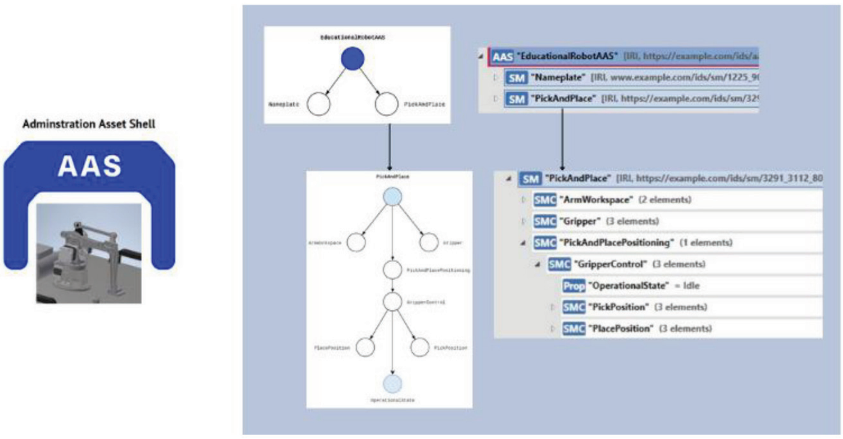

Figure 6. Structure of the AAS of the Educational Robot (Source: Authors own work)

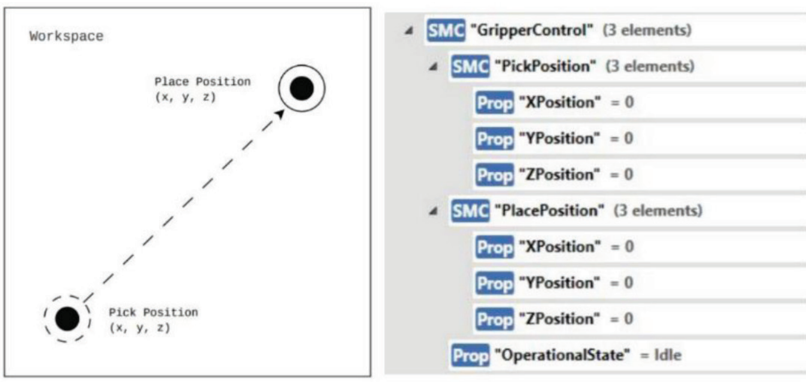

Figure 7. (a) Representation of the Robot´s Pick and Place Routine; (b) AAS Variables for Pick and Place (Source: Authors own work)

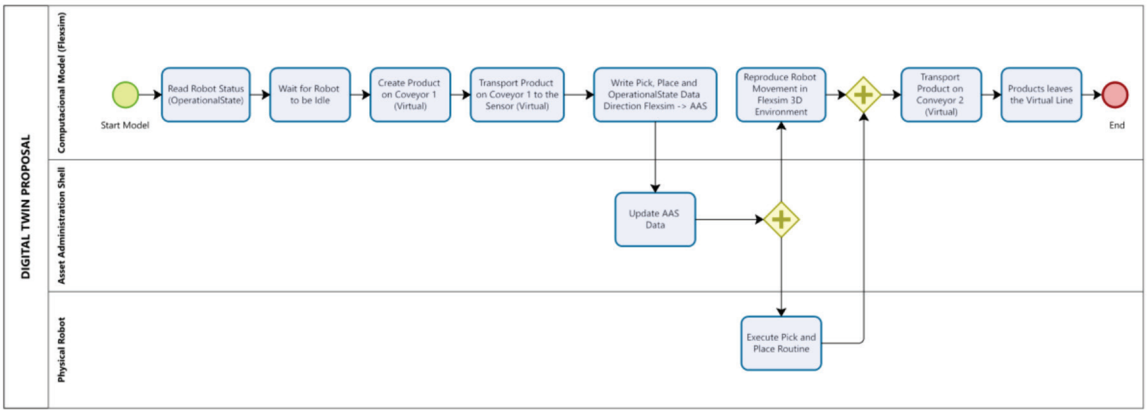

Figure 8. Flowchart of the Digital Twin Model Proposed for Postgrade Students (Source: Authors own work)

lessons taught by the professor, utilizing 3D environment elements. At the end of the module, this served as the practical exercise. Its development is mainly divided into two parts: the first involves building the 3D environment in FlexSim (Figure 9), and the second involves connecting the simulator to the robot's AAS using the FlexSim module called Emulation. Emulation is accessed through the Toolbox under the Connectivity option.

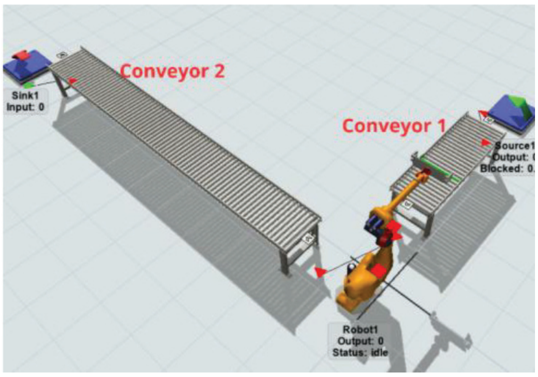

Figure 9. Proposed Computational Model for Classroom use using Flexsim´s 3D Environment (Source: Authors own work)

As previously mentioned, the connection is made using the OPC UA protocol, which should be selected in Emulation. The connection settings between the Computational Model and the Robot's AAS are shown in Figure 10.

Figure 11 shows the Gripper Control Submodel, which contains all the variables used in the developed Computational Model, including the Pick and Place variables with their respective X, Y, and Z values.

From Figure 11, we can also see other available AAS variables, such as "CurrentGlobalPosition," which provides the robot's current positioning. This enables another possible FlexSim model, where the simulator reads this variable and reproduces the ro-

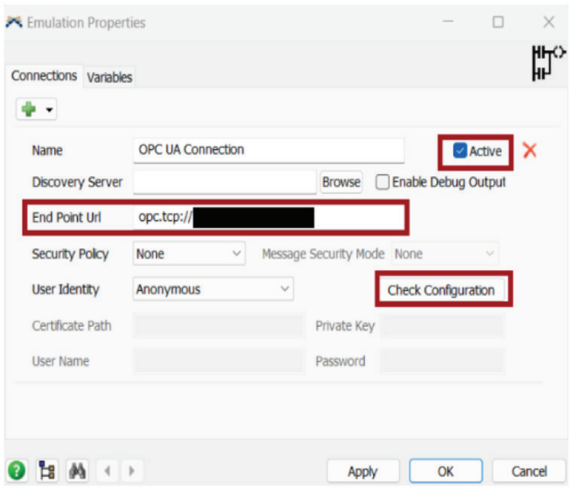

Figure 10. Configuration settings for the connection between the Computational Model and Robot AAS via OPC UA (Source: Authors own work)

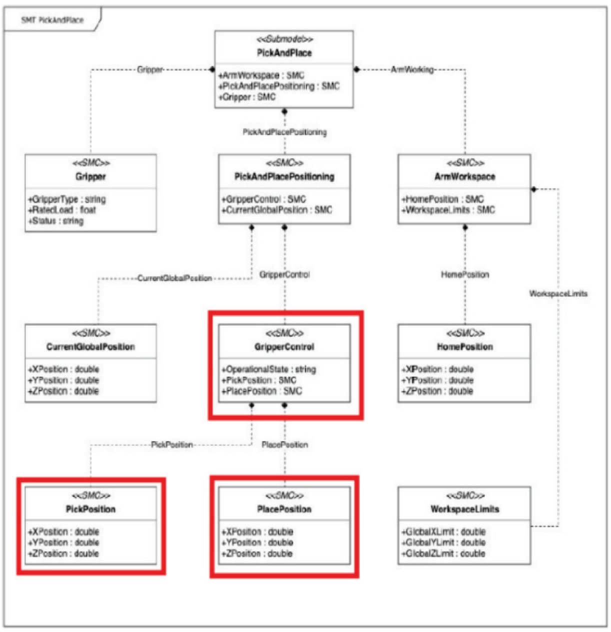

Figure 11. UML of the Pick and Place Submodel of the Educational Robot (Source: Authors own work)

bot's virtual position. This illustrates the prototype's versatility. However, for this postgraduate simulation module, a simpler application was proposed, one that fulfills the objective of real-time reading and writing using the Digital Twin concept. From this starting point, students can gain knowledge to create more advanced applications, such as integrating intelligent decision-making within the model. Figures 12 and 13 show evidence of laboratory testing between the Robot, AAS, and Simulation Model, as well as classroom use of the robots.

To understand the students' perception of the practical class in question, a form was developed to evaluate different aspects of the experience. The class had the participation of 24 students, and the form was answered voluntarily and anonymously, sent through institutional emails. In total, 22 responses were obtained, representing 91.67% of the class. To assess the students' level of understanding regarding the concepts covered in the class, two initial questions were formulated: 1. Before the practical activity, what was your perception of the concepts of Digital Twins, Asset Administration Shell (AAS), and Computational Simulation?, and 2. After the practical activity, how do you evaluate your understanding of these concepts? The responses were recorded on a scale of 1 to 5, where 1 represents "poor" and 5 "excellent." Before the activity, 72.7% of the students rated their understanding between levels 1 and 3 (medium to low). After the practice, this number dropped to only 9.1%, while 40.9% assigned a score of 4 and 50% the highest score (5), as shown in figure 14. Thus, there was a significant increase in the understanding of the presented concepts, with 90.9% of the students stating that they understood the content well by the end of the class.

Furthermore, 100% of the students stated that the practical class contributed to the consolidation of the theoretical content covered. Regarding engagement in the activity, the students rated it on a scale from 1 (not engaged) to 5 (very engaged), with 63.6% giving a rating of 5 and 36.4% a rating of 4. Regarding the impact of using the educational robot on the learning experience, the results were as follows: 77.3% of

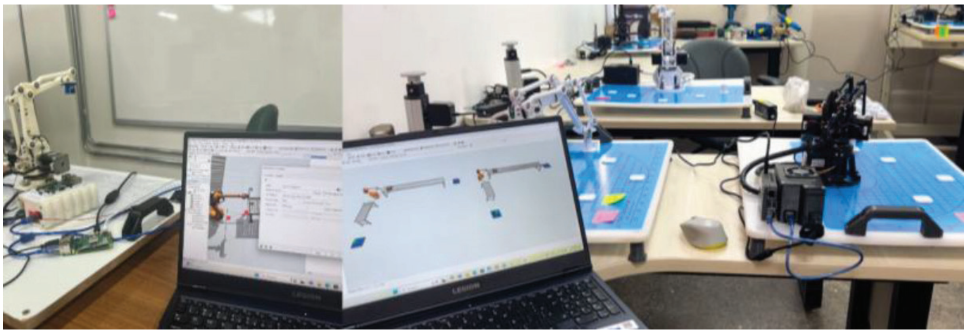

Figure 12. Evidence of the laboratory tests between the computational Model, Robot AAS and Physical Robot (Source: Authors own work)

Figure 13. Evidence of classroom application of concepts (Source: Authors own work)

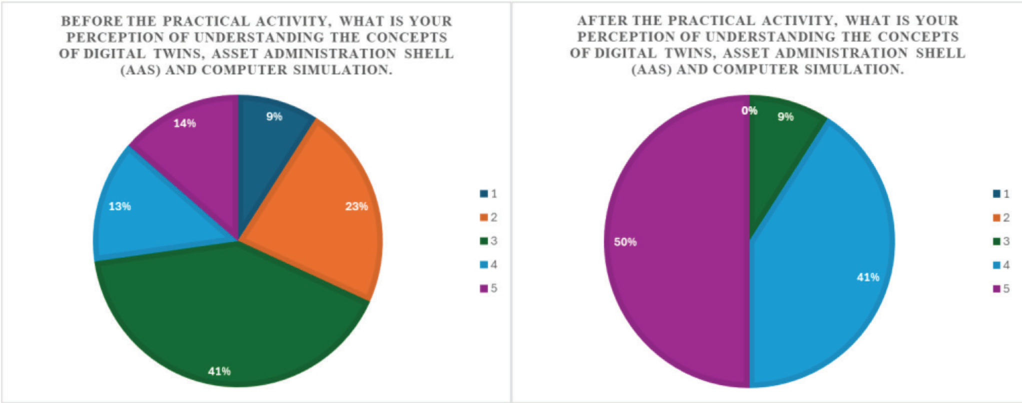

Figure 14. Student feedback on conceptual understanding before and after the class (Source: Authors own work)

the students considered the activity very interesting (grade 5); 18.2% gave it a grade of 4; 4.5% gave it a grade of 3. Furthermore, regarding the relevance of the practical activity for academic and professional training, 86.4% of the students rated it as highly relevant (grade 5), 9.1% as grade 4, and 4.5% as average (grade 3), indicating that the practice helped in the professional training of the students and the acquisition of Industry 4.0 skills. When asked if they believe that the educational robot and computer simulation could be applied in other courses or subjects, 95.5% responded positively. Finally, the students highlighted the main positive points and aspects to be improved in the activity. As a positive point, the most mentioned aspects were the availability of robots for practice and the visualization of concepts applied in the classroom. As for areas for improvement, the most recurring suggestions were the inclusion of more applications and scenarios using the robot and computer simulation, as well as an increase in the activity's execution time. Such results can be seen in Figure 15 below.

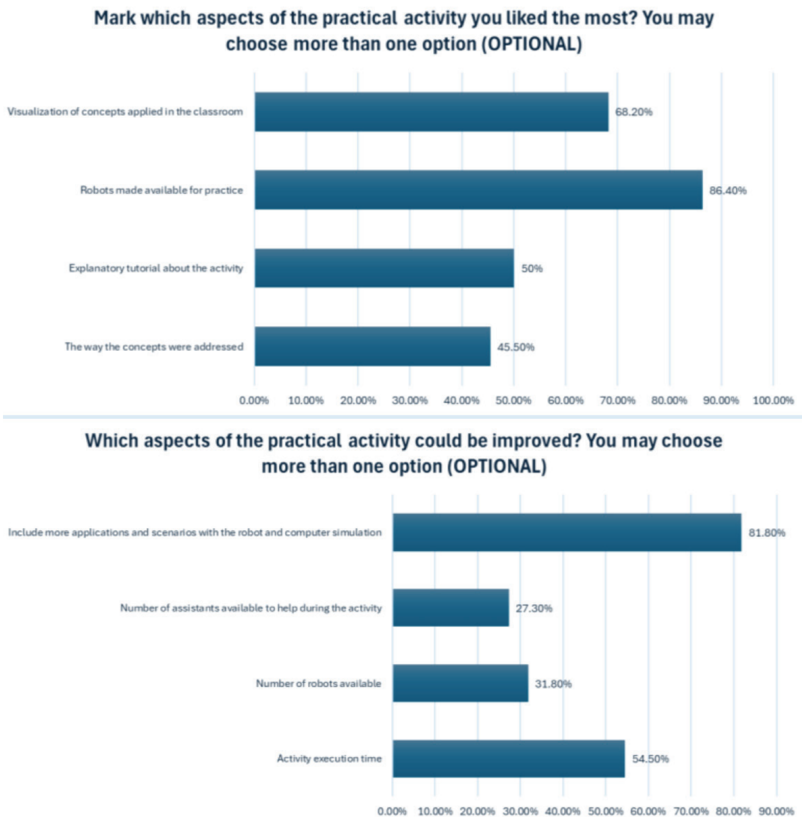

Figure 15. Student feedback on positive aspects and suggestions for improvement of the Hands-on Class (Source: Authors own work)

5. Conclusion

This study presented the development and implementation of an educational product aimed at teaching the fundamental concepts of Industry 4.0, using a 3D printed educational robot. The proposal developed sought to integrate active learning methodologies in engineering education to provide students with a dynamic learning environment in line with the demands of today's market. The structures available are essential to the teaching and learning process so that students can immerse themselves in the context of an automated industrial factory. The hands-on approach, combined with the use of computational simulation technologies, not only reinforced the presented concepts but also offered students a broad view of the stages involved in robotic process control, software engineering, and more.

The application of the educational robot proved effective in understanding Industry 4.0 concepts, enabling students to experience the challenges and possibilities of these emerging technologies in a controlled environment. The hardware, software and computer simulation together were able to provide in-depth experience in this environment and encouraged active learning and experimentation. The research reveals important results, some of which are highlighted below:

- Replicable Model: Offers a low-cost, open-source "learning factory" model that allows institutions in resource-limited settings to implement a learning environment aligned with the demands of Industry 4.0.
- Innovative Pedagogical Approach: Presents a new methodology for teaching the Digital Twin "meta-skill," focusing on developing AAS for interoperability.
- Methodological Validation: Validates mixed-methods research as an effective and robust methodology for evaluating and improving pedagogical interventions in engineering.

These findings demonstrate that the work not only answered the original research questions but also provides a roadmap and foundation for future projects aimed at aligning academic training with the practical needs of industries in the current scenario.

These observations underscore the need to expand the methodology to different contexts and evaluate its replicability in other educational institutions. Replicating this model in new educational settings can contribute to its validation and adaptation across various educational levels and fields of knowledge.

Future work may focus on expanding the application of this methodology across different courses and institutions to validate its replicability. Comparative studies between traditional and innovative methodologies are also suggested, along with a more in-depth analysis of the impact of this approach on developing the competencies and skills required by Industry 4.0. Adapting the model to new scenarios and extending the duration of the activity are also important areas to be explored. Finally, this work reinforces the importance of adopting innovative methodologies in engineering education and highlights the potential of Industry 4.0 technologies as didactic tools. It´s also worth noting that the research question was answered: the application of the educational robot in this study and context proved effective in supporting student engagement and the development of technical Industry 4.0 skills in engineering education. It´s hoped that this research will serve as a reference for the implementation of new educational projects aimed at aligning academic training with labor market demands, promoting more efficient and meaningful learning.

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