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Industrial Challenges for Automation Learning

J. Duque-Domingo[a,*], E. Zalama[a], J. Gómez-García-Bermejo[a]

[a] ITAP-DISA. Universidad de Valladolid. Spain

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Resumen

Este artículo describe una actividad de aprendizaje en Automática basada en un desafío industrial real propuesto en el marco de la colaboración entre una universidad y una entidad privada, concretamente la fábrica de Michelin en Valladolid. La actividad se diseñó como una experiencia competitiva y de aprendizaje basado en problemas, donde equipos de estudiantes formularon soluciones aplicando robótica, visión por computador, control e inteligencia artificial. De 36 equipos inscritos, 25 entregaron una propuesta final, 4 pasaron a la fase de defensa final y un equipo resultó ganador. Los equipos finalistas visitaron in situ instalaciones industriales, lo que reforzó la conexión entre la formación universitaria y las restricciones reales de implantación. La percepción educativa de la actividad se exploró mediante una encuesta anónima respondida por 30 estudiantes individuales. Los resultados mostraron una percepción positiva de la experiencia, especialmente en motivación, implicación activa y trabajo en equipo. Los resultados apoyan el valor educativo de incorporar problemas reales de la industria en asignaturas del área de Automática.

Palabras clave: Educación en automática, aprendizaje basado en problemas, robótica, visión por computador, inteligencia artificial, transferencia universidad-empresa

Industrial Challenges for Automation Learning

Abstract

This paper presents an automation learning activity built around a real industrial problem proposed within a university-private sector collaboration, specifically the Michelin factory in Valladolid. The experience was conceived as a problem-based, competitive learning activity rather than as a conventional classroom exercise. Student teams had to analyse an authentic production-related challenge and prepare a technically grounded proposal involving robotics, computer vision, control engineering and artificial intelligence. The activity attracted 36 registered teams; 25 submitted a proposal, 4 reached the final defence stage, and one team won the competition. The finalist teams visited the industrial facilities, which helped students understand operational constraints, safety requirements and implementation feasibility. Participants' perception of the educational value of the activity was explored through an anonymous questionnaire completed by 30 individual students. Results indicate a positive perception of the activity, with high scores for motivation, active involvement and teamwork. The paper discusses the learning design, the role of generative AI as a support tool, and the value of real industrial challenges for automation education.

Keywords: Automation education, problem-based learning, robotics, computer vision, artificial intelligence, industrial challenges

1. Introduction

Engineering education in automation is increasingly expected to connect mathematical and technological foundations with authentic industrial decision-making. Graduates in industrial electronics, automation and robotics must not only understand sensors, actuators, programmable logic, control ar-

*Autor para correspondencia: jaime.duque@uva.es

chitectures and perception algorithms; they must also be able to judge whether a proposed solution is feasible in a plant, maintainable by technical staff, safe for operators and valuable for the organisation that adopts it. This need is consistent with the broader shift in engineering education from content transmission to active, design-oriented and problem-based learning (Prince and Felder, 2006; Yadav et al., 2011). Real industrial problems are particularly useful in the automation area because they expose students to constraints that are normally difficult to reproduce in laboratory practice: incomplete information, physical variability, space limitations, integration with existing machinery, cost pressure, safety requirements and the need to communicate solutions to non-specialist stakeholders. Such constraints transform the activity from an exercise in applying a known method into a professional reasoning task. In this context, a learning activity based on an industrial challenge can help students understand that a technically elegant algorithm is only one part of an implementable automation solution. The activity analysed in this paper was developed in the framework of a university learning initiative in collaboration with a private industrial organisation. The aim was to encourage students to address a realistic production challenge through the combined use of robotics, computer vision, control engineering and artificial intelligence (AI). Although the activity adopted a competitive format, it is presented here primarily as an educational intervention: a structured learning experience in which students had to move from problem interpretation to solution design, final defence and reflection on feasibility. A distinctive element of the experience was the explicit acceptance of AI-based support during the preparation of the proposal. Generative AI tools can accelerate information search, help students compare design alternatives, improve the structure of technical reports and assist in the preparation of visual material. However, they also create the risk of producing plausible but poorly understood proposals. For that reason, oral defence, discussion with evaluators and feasibility-oriented questions were maintained as essential assessment mechanisms. This approach aligns with emerging AI literacy frameworks that emphasise critical and responsible use of AI, not merely access to the tools (Long and Magerko, 2020; Southworth et al., 2023; UNESCO, 2025).

2. Learning activity design

The learning activity was structured around a real industrial challenge and a short development cycle. The official rules defined a sequence with registration, publication of the industrial problem, development of solutions, oral presentation and award decision. The assessment criteria combined technical and communication aspects, specifically focusing on technical innovation and originality (40 %), technical rigor and documentation quality (25 %), technical and economic feasibility (25 %), and sustainability, ethics, regulations, and safety (10 %). Furthermore, the final evaluation also took into account the quality of the oral presentation and the effectiveness of the Q&A session. The final oral presentation was limited to a short pitch followed by questions, forcing teams to prioritise the most relevant technical decisions and evidence. From an educational perspective, this structure has several advantages. First, it gives students a bounded but authentic problem, which reduces the ambiguity of an open innovation contest while preserving the realism of an industrial need. Second, it promotes teamwork and task distribution. Third, it requires integration of different areas of automation rather than isolated knowledge: mechanical constraints, robotic manipulation, perception, control, safety, software architecture and deployment. Fourth, it introduces students to the professional culture of defending an engineering proposal before evaluators who value usefulness and viability as much as technical novelty. The activity can be interpreted through four learning moments. The problem launch provided the industrial context and forced participants to clarify the operational need. The team development phase required students to connect automation concepts with robotics, vision and control design. The final defence validated understanding through a concise pitch and technical questions. Finally, the industrial visit exposed finalist teams to real facilities, helping them link their proposals to space constraints, safety rules, operator routines and implementation feasibility. The challenge statement was intentionally left at a level that required interpretation. Students had to identify what information was essential, what assumptions were reasonable and which parts of the solution could be specified at conceptual level without overclaiming industrial readiness. Compared with many conventional laboratory activities, especially those based on predefined inputs, outputs and validation procedures, this challenge placed greater emphasis on problem framing, assumption management and feasibility reasoning. In the present activity, uncertainty was deliberately incorporated as an explicit design feature, particularly through incomplete industrial information, the need to formulate assumptions and the absence of a single predefined solution. The industrial visit of the four finalist teams was especially relevant. In many university activities, students work from a written statement and never see the environment in which a solution would operate. In this case, visiting the facilities provided first-hand evidence of constraints such as available space, operator routines, equipment interfaces, safety procedures, production rhythm and the need to minimise disruption. These observations helped students understand why industrial automation design is not only a matter of selecting hardware or algorithms, but of fitting a solution into an existing socio-technical system. The activity attracted 36 registered teams (108 participants). Of these, 25 (75 participants) submitted a final proposal, 4 (12 participants) were selected for the final stage and 1 obtained the winning position. Three prizes were granted, and travel costs were also covered. The present educational analysis combines three sources of evidence: the activity structure, the progression of teams through the different stages, and a post-activity questionnaire completed by 30 participants. The questionnaire was based on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The eight questionnaire items addressed three analytical dimensions. The first dimension, design fit, included challenge complexity, organisation and time availability. The second dimension, engagement and teamwork, included active involvement, team dynamics and the overall stimulating character of the activity. The third dimension, support and resources, included technical mentoring and technological resources. Given the exploratory nature of the study and the limited sample size, only descriptive statistics were calculated. The goal was not to infer causal effects, but to document whether participants perceived the activity as pedagogically useful. The questionnaire was answered by 30 individual participants. Responses were anonymous and were not linked to team identifiers; therefore, it was not possible to determine how many responses came from each team. Consequently, the survey results should be interpreted as individual perceptions of the activity rather than as independent team-level observations. Since several students may have belonged to the same team, some correlation between responses cannot be ruled out. For this reason, the analysis was limited to descriptive statistics and no inferential claims were made.

2.1. Role of AI in proposal development

The activity explicitly allowed students to use AI-based tools as support during the development of the proposal. Their use was framed as an engineering aid rather than as a substitute for technical judgement. Students could use generative AI to explore concepts, compare alternative architectures, refine written explanations, prepare presentation structures and identify possible risks. Nevertheless, teams were expected to justify their own decisions, explain assumptions and respond to questions. This design choice is important because the professional value of AI in engineering depends on critical supervision, domain knowledge and validation against real constraints (European Union, 2024; UNESCO, 2025). This AI-supported workflow also created opportunities for metacognition. When students used AI-generated suggestions, they had to decide which ideas were compatible with the industrial environment and which were generic or unrealistic. In the classroom discussion, this distinction was emphasised as a professional competence: engineers must be able to transform abundant information into technically justified decisions, not merely collect plausible options. The oral defence therefore played a dual role. It assessed communication skills, but it also helped verify whether students understood the proposal they had prepared. This is especially relevant when generative tools can produce coherent text and diagrams quickly. In an automation education context, the decisive competence is not only producing a plausible proposal but being able to defend why a sensing strategy, control architecture, robot configuration or computer vision pipeline is appropriate for the problem. However, the study did not collect systematic evidence on how students actually used generative AI tools during the activity. Therefore, it is not possible to determine whether AI was mainly used for documentation, ideation, comparison of technical alternatives, programming support, vision-related design or presentation preparation. This limitation is relevant because AI is presented as one of the distinctive elements of the activity. Future editions will include specific questionnaire items and/or short reflective reports asking teams to document the type, frequency and perceived usefulness of AI use, as well as how AI-generated suggestions were technically validated, modified or discarded.

3. Results

3.1. Team progression and educational reach

The participation data show that the activity reached a substantial number of student teams and maintained a high level of commitment. The ratio between final proposals and registered teams was 69.4 %, which is relevant considering that the problem required an integrated technical response within a compressed schedule. The selection of four finalist teams created a manageable final stage while preserving a high level of recognition and feedback for the best proposals. The fact that one team obtained the winning position was less important pedagogically than the process by which many students analysed a real industrial problem and converted it into an automation proposal. The progression data also show that the activity worked as a filter of technical maturity. Registration reflected initial interest, final submission reflected sustained effort, and selection for the final stage reflected the ability to communicate a coherent automation concept. This progression is useful pedagogically because it creates different levels of achievement without excluding the learning value of non-finalist proposals. The submitted proposals typically combined conceptual design with implementation considerations. Successful teams did not limit their work to describing a robot, a camera or a controller. Instead, they tended to include workflow analysis, perception requirements, actuation alternatives, safety considerations, data needs, integration with industrial equipment and expected benefits. This is precisely the type of systems thinking that is difficult to promote through isolated laboratory exercises.

3.2. Survey results

The questionnaire results are summarised graphically in Figure 1. The global mean score across all items was 3.95 out of 5 (SD=1.17), indicating a generally positive perception of the activity. The strongest items were active involvement (M=4.40), team dynamics (M=4.33) and challenge complexity (M=4.07). The lowest score corresponded to technical support and mentoring (M=3.20), with only 43.3 % agreement. This result indicates that the mentoring structure was the clearest weakness of the activity. The open nature of the challenge and the compressed development period may have made it difficult for some teams to validate assumptions, assess feasibility or receive timely feedback on technical decisions. Therefore, this item should not be interpreted as a minor organisational issue, but as a central design aspect to be improved in future editions. At item level, the agreement rates were 80.0 % for challenge complexity, 60.0 % for organisation, 70.0 % for available time, 90.0 % for active involvement, 86.7 % for team dynamics, 43.3 % for mentoring and support, 70.0 % for technological resources and 80.0 % for the overall stimulating character of the activity. These values show that the activity was perceived as demanding but motivating, while the mentoring structure was the clearest point for improvement. The survey was carried out prior to the selection of finalists to ensure that the questions remained unaffected. The descriptive statistics should be read together with the nature of the task. A real industrial problem introduces productive discomfort: students must work with partial information, justify assumptions and accept that several solutions may be possible. The positive overall mean therefore suggests that this uncertainty did not prevent engagement; instead, it appears to have contributed to the perception that the activity was meaningful and close to professional practice.

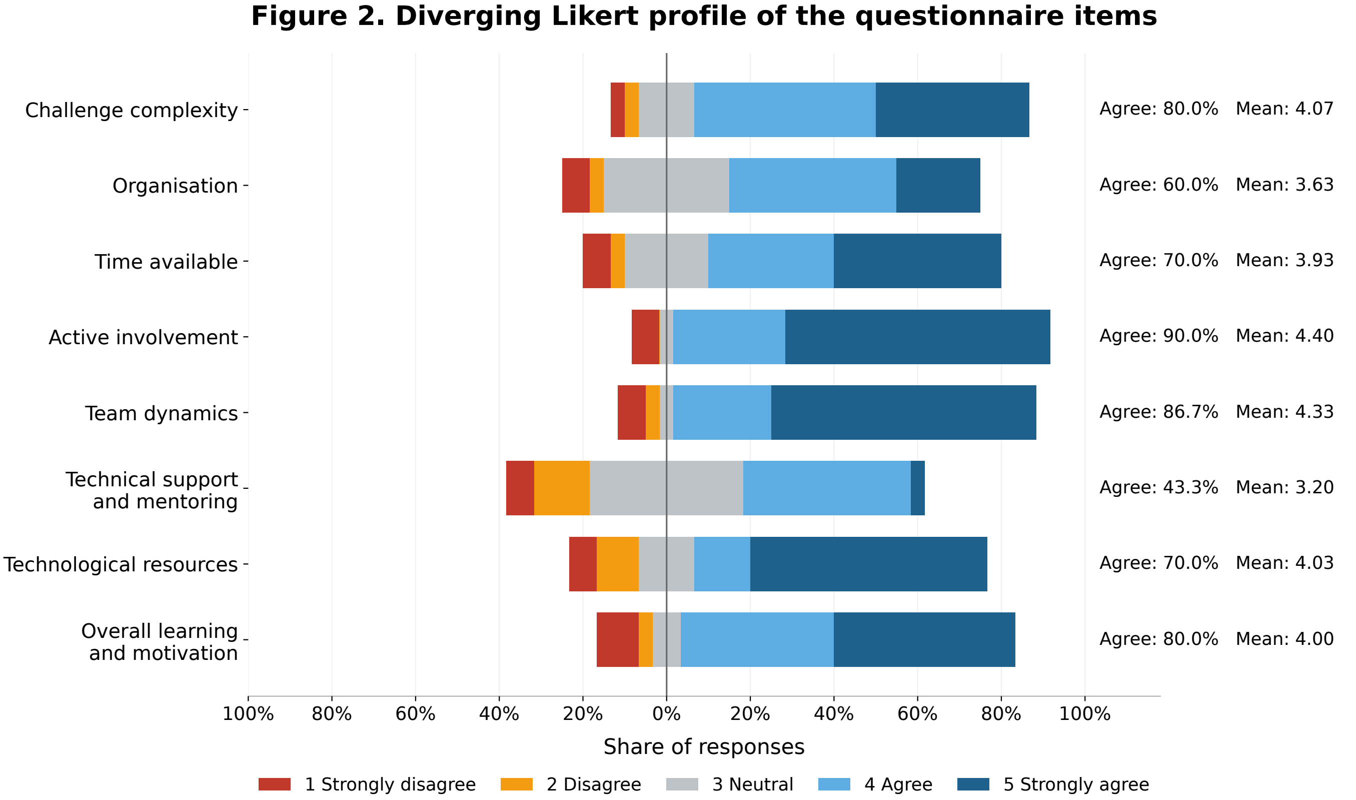

Figura 1: Agreement and mean scores for each questionnaire item.

The item-level distribution reveals a nuanced interpretation. Participants clearly valued the motivational and collaborative dimensions of the activity: 90.0 % agreed or strongly agreed that they were actively involved, 86.7 % agreed or strongly agreed that team dynamics supported participation, and 80.0 % considered the experience stimulating. These results are consistent with project-based learning literature, which emphasises autonomy, collaboration and meaningful tasks as drivers of engagement (Prince and Felder, 2006; Yadav et al., 2011). The time available and organisational aspects received positive but more moderate values. This is expected in a compressed industrial challenge: limited time increases intensity and authenticity, but it also generates pressure and uneven access to information. The mentoring item was the weakest, with 43.3 % agreement, and should be interpreted as a design improvement signal. In future editions, mentoring could be structured through scheduled technical checkpoints, short feasibility templates and targeted guidance on safety, sensing and integration constraints. When items were grouped by analytical dimension (see Figure 2), engagement and teamwork achieved the highest aggregated mean (M=4.24), followed by design fit (M=3.88) and support/resources (M=3.62). This distribution suggests that the activity was very effective in generating student commitment and collaborative learning, while the technical support structure requires further refinement. For automation education, this distinction is important: motivation alone is not sufficient, but it creates favourable conditions for deeper learning if supported by adequate technical scaffolding.

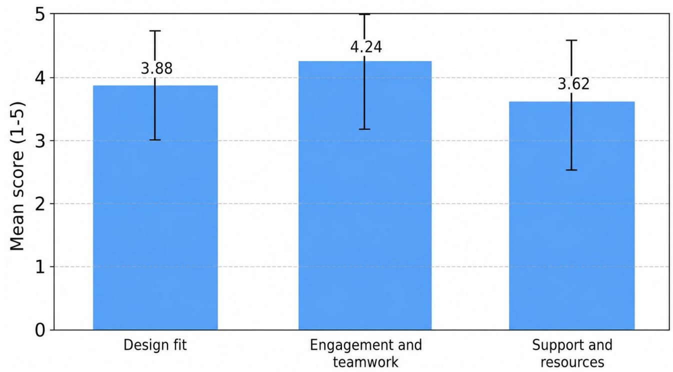

Figura 2: Aggregated agreement by learning dimension.

4. Discussion

The results suggest that participants perceived the industrial challenge as a valuable learning experience, particularly in terms of motivation, active involvement and teamwork. However, the evidence should be interpreted as perception-based and exploratory, rather than as an objective measurement of learning gains. First, the activity encouraged students to integrate knowledge from different areas. A realistic automation proposal cannot be solved by a single discipline: the design of robotic manipulation depends on mechanical constraints, perception depends on lighting and data variability, control depends on real-time behaviour, and industrial deployment depends on safety and maintainability. By requiring teams to present a complete concept, the activity moved students towards system-level reasoning. Second, the activity helped students become familiar with the industrial world. The finalist visit was not a symbolic prize but an educational component. Seeing the production environment helped students understand that companies evaluate ideas according to feasibility, impact, scalability and operational risk. This type of contact is valuable for employability because it exposes students to the language and priorities of industry before they enter internships or professional positions. It also helps them recognise the difference between an attractive prototype and a robust solution that can be deployed in a plant. Third, the use of AI tools introduced a timely pedagogical issue. In engineering education, banning generative AI is neither realistic nor aligned with current professional practice. A more productive approach is to design tasks in which AI can support documentation, ideation and comparison, while assessment focuses on understanding, judgement and defence. In this activity, AI was beneficial when used to broaden the range of alternatives, improve the structure of the proposal and accelerate communication tasks. However, the final value of the proposal still depended on students' ability to explain assumptions, validate feasibility and connect the idea to automation principles. Fourth, the activity contributed to entrepreneurial and innovation-oriented competences. Although the goal was not to create start-ups, students had to consider whether their solutions generated value for an industrial user. This is aligned with engineering education recommendations that stress the importance of opportunity recognition, professional judgement and understanding the social and economic context of engineering decisions (National Academy of Engineering, 2004; Duval-Couetil et al., 2012). For instructors, the main design implication is that challenge-based activities require careful balance. Too much guidance would turn the problem into a closed exercise and reduce authenticity; too little guidance can make students focus on presentation quality instead of technical feasibility. The results suggest that a small number of structured checkpoints could improve the technical depth of the proposals while preserving the benefits of autonomy and creativity. This is particularly important because technical support and mentoring was the lowest-rated questionnaire item. A more structured mentoring model could include three short checkpoints: first, problem interpretation and assumptions; second, system architecture and feasibility; and third, validation strategy, risk identification and safety considerations. These checkpoints should not provide a predefined solution, but should help teams detect unrealistic assumptions and improve the technical consistency of their proposals. The main limitation of the study is the descriptive nature of the evidence. The survey captured participants' perceptions immediately after the activity but did not measure long-term learning outcomes, technical competence gains or transfer to later projects. Moreover, the questionnaire was short and focused on general experience rather than detailed conceptual learning. Future iterations should combine perception data with rubric-based assessment of proposals, interviews with participants, and follow-up analysis of whether the activity influences final-degree projects or internships. A further implication concerns assessment. If the activity is evaluated only through the final ranking, the educational value of the intermediate process may be underused. A richer assessment model could combine the final defence with formative checkpoints on problem analysis, risk identification, system architecture and validation strategy. This would help students understand that industrial automation requires an iterative process of specification, testing and refinement, not only an attractive final presentation. This study has several limitations. First, the questionnaire was anonymous and responses were not linked to team identifiers. As a result, it was not possible to determine whether the 30 responses were evenly distributed across the 25 teams that submitted final proposals. Some intra-team correlation between responses may therefore exist. Second, the evaluation was based on students' perceptions and did not include objective pre/post measures of learning gains or an external assessment of technical competence acquisition. Consequently, the results should not be interpreted as evidence of measurable improvement in automation competence. Third, although the use of generative AI was explicitly allowed and discussed as part of the learning design, the study did not collect specific empirical data on how students actually used AI tools. Future editions should address these limitations by linking survey data to teams in anonymised form, incorporating rubric-based evaluation of submitted proposals, adding specific questions on AI use, and analysing whether participation influences later academic projects or internships.

5. Teaching implications

The experience suggests several practical recommendations for instructors who want to introduce similar activities in automation-related subjects. The first recommendation is to define the industrial problem with enough specificity to make the work technically grounded, but without converting it into a closed exercise with one expected answer. Students should receive information about the process, relevant constraints and expected impact, while still being responsible for formulating assumptions, identifying missing data and selecting an appropriate solution strategy. This balance is essential for preserving authenticity. The second recommendation is to make feasibility an explicit learning outcome. In automation, students often focus on the visible part of a proposal, such as the robot, the camera, the controller or the AI model. However, industrial feasibility also depends on integration with existing equipment, maintainability, operator acceptance, safety certification, data availability and robustness to disturbances. A simple feasibility checklist used during the development phase could help teams avoid overly generic proposals and could improve the quality of the final defence. The third recommendation is to structure mentoring without eliminating autonomy. The survey results indicate that students valued the activity but perceived mentoring as the weakest dimension. This does not necessarily mean that the activity required continuous supervision. Rather, it suggests that a short challenge benefits from scheduled points where teams can test their assumptions against expert feedback. For example, one checkpoint could focus on the interpretation of the industrial need, a second on the proposed architecture, and a third on validation and risk mitigation. The fourth recommendation concerns the use of generative AI. Instead of treating AI as an external shortcut, it can be integrated as an object of reflection. Students can be asked to document how AI helped them generate ideas, improve communication or compare technologies, and also to identify which AI suggestions were discarded because they were not compatible with the real context. This practice reinforces AI literacy and makes explicit the difference between assistance and authorship. To make this reflection assessable, future editions should include a short AI-use statement in which each team explains which tools were used, for what purposes, which outputs were accepted or rejected, and how the final technical decisions were validated by the students. Finally, the activity can be connected to later academic milestones. Final-degree projects, internships and master-level projects often require students to define objectives, communicate with stakeholders and justify design choices. A challenge-based activity carried out before those milestones can act as preparation, especially if students receive feedback not only on the final pitch but also on the technical reasoning behind their decisions. In this sense, the activity should be understood as part of a broader curriculum strategy for professional readiness in automation engineering.

6. Conclusions

This paper has described a university learning activity in automation based on a real industrial challenge proposed in collaboration with the private sector. The activity required students to develop and defend solutions involving robotics, computer vision, control engineering and AI. The participation flow - 36 registered teams, 25 final proposals, 4 finalists and 1 winning proposal - shows that the format was capable of mobilising significant student effort around an authentic problem. The finalist visit to industrial facilities reinforced the educational value of the experience by exposing students to real operational constraints. Furthermore, the winning team participated in the "Jornadas de Automática", a national event of significance within the field of automation. The anonymous survey completed by 30 individual participants showed a positive overall perception, especially in active involvement, teamwork and motivation. However, because responses were not linked to team identifiers, the results should be interpreted as individual perception data and not as independent team-level evidence. At the same time, the lower score for mentoring and support identifies a clear area for improvement. The experience suggests that real industrial challenges can be highly valuable in automation education when they are framed not only as competitions, but as structured learning activities with explicit objectives, feedback, feasibility criteria and opportunities for reflection. AI tools can further enrich the process when their use is accompanied by oral defence and critical evaluation. Future work will refine the mentoring model through scheduled technical checkpoints, improve the survey instrument by including specific items on AI use, and analyse the quality of technical proposals with more detailed rubrics. Future editions should also incorporate evidence beyond perception data, such as rubric-based assessment, reflective reports and follow-up indicators related to later projects or internships. From a curricular perspective, the experience can be positioned between conventional laboratory work and internships. Laboratory sessions remain necessary because they provide controlled practice with specific technologies, but they do not always expose students to the ambiguity of industrial decision-making. Internships provide that exposure, but they are not always available to all students at the same moment in the curriculum. A real industrial challenge organised within the university can therefore act as an intermediate pedagogical device: it preserves academic supervision while introducing professional constraints. The activity also contributes to the development of transversal competences that are difficult to evaluate through written examinations. Students had to distribute tasks within the team, select relevant information, negotiate design alternatives, prepare a coherent narrative and defend the proposal in public. These competences are central in automation engineering because industrial projects normally involve multidisciplinary teams and stakeholders with different priorities. In this sense, the learning value of the activity lies not only in the final technical solution but also in the process of collaborative engineering reasoning. Future editions should strengthen the connection between the challenge and formal assessment rubrics. A rubric including problem understanding, system architecture, automation feasibility, AI use, validation strategy, communication and reflection would make expectations clearer and would allow more systematic comparison across teams. It would also help distinguish between creative but immature ideas and proposals that show a balanced understanding of technical, operational and economic constraints.

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