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Estimating the Impact of Industry 4.0 Automation on Curricular Competence Indicators in Brazilian Vocational Education and Training: A Mixed-Methods AI-Supported Analysis

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Abstract

Context: The Fourth Industrial Revolution has accelerated the integration of automation technologies into the world of work, raising important questions about the future of Vocational Education and Training (VET). While existing literature has primarily focused on the labor market impacts of automation, few studies have investigated its direct effects on VET curricula. This article addresses this gap by assessing how automation may influence the structure and content of technical courses offered by Brazil's National Service for Commercial Apprenticeship (Senac), one of the country's largest VET providers.

Approach: We implemented a three-stage methodology to estimate the impact of automation on technical education: (i) Technological mapping, (ii) prompt development, and (iii) assessment. In the third stage, we combined human expertise with generative Artificial Intelligence tools (GPT-4 and Claude 2) to evaluate 2,100 Course Competency Indicators (CCIs) across 35 technical courses. This dual approach enabled a scalable yet context-sensitive analysis, leveraging both the depth of human judgment and the efficiency of AI.

Findings: The technological mapping identified seven key categories of automation technologies: 3D/4D Printing and Modeling, Applied AI, Data Analytics, Digital Platforms and

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Applications, Extended Reality, IoT and Connected Devices, and Robotics. The developed prompt provided structured guidance for assessing automation impact on CCIs, including instructions for classifying technologies, estimating impact levels, and justifying the results. The assessment showed that 70.3% of the CCIs are at Medium (39.1%) or Low (31.2%) levels of automation impact, suggesting that the courses remain current and relevant, challenging the narrative of rapid obsolescence in technical education. Digital Platforms and Applications were the most frequently cited technology, appearing nearly three times more often than Applied AI and Data Analytics. In contrast, 3D/4D Modeling and Extended Reality had limited relevance in the current course content.

Conclusions: This research contributes to global discussions on the future of VET in the context of rapid technological change. It also highlights how automation risk assessments can support curriculum development by identifying where updates or innovations are most needed. Strengthening the alignment between training programs and emerging labor market demands will be essential to ensuring inclusive, future-oriented vocational education.

Keywords: Automation, Vocational Education and Training, VET, Large Language Models, LLM, Future of Work, Artificial Intelligence

1 Introduction

The contemporary era is marked by the 4th Industrial Revolution, a phase of development that emphasises the integration of advanced technologies such as Artificial Intelligence (AI), Robotics, Big Data, and the Internet of Things (IoT) in different sectors of the economy. Just as in previous industrial revolutions, it is essential to deal with the changes caused by introducing new technologies to maintain employment levels while reaping the benefits of technology adoption. These ongoing transformations redefine production and management standards and significantly reverberate in the educational domain, especially VET, requiring an update of courses' curricula and institutions' course portfolio structures to align student training with the job market demands. As such, we ground our research in the view that VET needs to keep up with the changes in the world of work at the same time that it actively changes how work is done (Markowitsch & Hefler, 2018).

This research proposes a methodology for evaluating the impact of automation on technical courses. The objective is to assist educational institutions in preparing students for the job market, considering the challenges that automation is expected to bring in the coming years. The methodology allows us to estimate the impact of automation on each course and to establish a relationship between specific emerging technologies and VET.

For this purpose, the study focuses on the National Curricular Plans (NCPs) of the National Service for Commercial Apprenticeship (Senac)[1], one of Brazil's largest VET institutions, serving over 1.6 million enrollments annually across 600+ units in the country. For each technical course, the impact will be evaluated on the Course's Competency Indicators (CCIs) to understand how the Course Curricular Units (CCUs) within the institution's NCPs may be updated to address technological changes and their impact on work.

This study addresses the challenge of understanding how automation technologies may affect VET programs, particularly in terms of course content and future relevance. The research is guided by the following question: How can the impact of automation on VET courses be systematically assessed using both expert judgment and artificial intelligence? To address this, the methodology is divided into three main parts: a) technological mapping, which involves defining, based on secondary sources, the categories of automation technologies most relevant to the segments served by Senac; b) rubric writing, which entails creating a set of rules to explain and organise the reasoning to be followed by those evaluating the impact of technologies, serving as both instructions for human evaluations and as prompts for AI; c) automation impact assessment, based on human assessment for a subset of courses used to refine the rubric and provide examples for the AI prompt, which evaluates all courses.

This paper is structured in six sections: Section 2 presents some background evidence context studies. Section 3 describes the methodology. Section 4 presents the impact of automation on Senac's technical courses, highlighting the stages of technological mapping and rubric writing. Section 5 discusses these results. Finally, Section 6 concludes the paper, considering its limitations and potential future work.

2 Evaluating the Impact of Automation: A Background

Concerns regarding the impact of automation have existed since the First Industrial Revolution, when large steam machines were introduced in newly created factories (Landes, 1969). The current Fourth Industrial Revolution has brought significant advances in technologies such as IoT, AI, and Robotics, emphasising their combined applications and transformative potential across all productive sectors (Schwab, 2016).

Recently, the launch of ChatGPT at the end of 2022 represented a significant advance in the ease with which end users access and use AI, allowing its popularisation and broad application to diverse tasks (Gmyrek et al., 2023) and opening new paths for making scientific advances in various fields of research. In the case of studies on the impact of automation on work, GPT has a double effect. First, it intensifies the impact of automation on highly educated workers and high-income roles (Eloundou et al., 2023; Gmyrek et al., 2023). Second, it emerges as a new tool for data analysis, as used here.

1 Portuguese acronym for Serviço Nacional de Aprendizagem Comercial.

GPT was methodologically used for the first time (as identified in our research) to analyse the impact of automation technologies on work by researchers from OpenAI (Eloundou et al., 2024). The authors developed an evaluation rubric and used GPT-4 to understand the potential of Large Language Models (LLMs) and LLM-based systems to reduce execution time without loss of quality of 19,265 tasks related to occupations described by the Occupational Information Network (O*NET). A human assessment of 2,087 detailed work activities – descriptions of professional activities that may be linked to one or more occupation-specific tasks – was used as inputs to prepare the prompt, which demonstrated high accuracy in the evaluation when compared to human experts. The results indicated that about 80% of the US workforce could see at least 10% of their work tasks impacted by the introduction of LLMs, while 19% of workers could experience at least 50% of their work tasks impacted. Furthermore, the authors found that the impact of LLMs would affect workers across the spectrum of education and income, with a more pronounced effect on those with higher education and income (Eloundou et al., 2024).

Similarly, the International Labor Organization (ILO) used GPT-4 to evaluate 3,123 tasks and 436 occupations using the international occupation classification table (ISCO-08) (Gmyrek et al., 2023), allowing to compare employment outcomes in high-income and low-income countries. The authors observed that GPT-4 could describe tasks related to ISCO-08 occupations comparable to human experts, consistently scored activities with high and low impacts, and provided reasonable justifications for the scores assigned. Additionally, the authors ran 100 assessments for 5 randomly selected tasks, finding high consistency between assessments for each task with a maximum standard deviation of 0.05, demonstrating that GPT-4 would have a lower element of randomness in their assessments than would be expected from human experts.

From a different perspective, Chen et al. (2023) investigated the likelihood of Chinese occupations experiencing a disruptive shock due to LLMs' widespread availability and use. The authors used all descriptors from the Chinese occupation dictionary, which included the description of each occupation, the content, the format, and the scope of the work activities. Three different LLM models (GPT-4, InternLM, and GLM) were used alongside 21 experts in AI and Economics to evaluate the major occupational groups in the Chinese classification. The authors found substantial positive correlations between the experts' assessments and those of the models. The results show that Chinese occupations with higher education, relatively high salaries, and white-collar occupations are more exposed to LLMs.

Eisfeldt et al. (2023) explored the relationship between this impact and the market value of companies. The authors evaluated the 19,265 tasks listed by O*NET, as in Eloundou et al. (2024). However, they used ChatGPT instead to evaluate whether ChatGPT could do the tasks in its current version or by future versions with additional capabilities. The authors crossed this data with information about the occupational structure of each company from public data on employee profiles. As a result, they observed that the types of occupations most impacted would be those involving non-routine cognitive tasks and workers in higher income brackets.

Based on this evidence, this work focuses on the direct relationship between VET and automation impact. As in Chen and Lee (2019), we use more than one LLM model (GPT-4 and Claude 2) to improve the quality of results obtained if only one model is used. However, unlike the previous study, we did not run the same evaluation once on each model but instead asked the second model to evaluate the results of the first and correct any discrepancies. We also followed the ILO recommendations (Gmyrek et al., 2023) by additionally asking GPT-4 to describe how each CCI would be automated, bringing transparency to the process; a challenge for the field of AI research (Braga et al., 2024).

3 Methodology

This section presents the methodological approach adopted in the study. Section 3.1 describes the database used, including its structure and relevance to the research objectives. Section 3.2 details the procedures developed to assess the impact of automation on vocational education, combining expert evaluations and large language models (LLMs).

3.1 Database

The estimated impact of automation on technical courses is possible due to the Senac Pedagogical Model (MPS), which is an approach that allows students to learn by doing and analysing their own practices. The MPS was created in 2013 to provide unity in the actions of all 27 Senac Regional Departments through a movement of pedagogical alignment. In this way, the MPS brings together a set of concepts that guide the pedagogical practices of the entire institution at a national level (Senac, 2015b).

The NCPs, which serve as input for evaluating the impact of automation on the institution's technical courses, present the curricular architecture of each Senac course. Every NCP covers the following topics: Course identification, requirements, and forms of access; justification and objectives; the graduate's professional profile (duties, skills, and training marks); and curricular organisation (detailed descriptors and CCIs).

Here, it is worth briefly presenting the concept of competence, which, for Senac, can be defined as: "observable, potentially creative professional action/doing, which articulates knowledge, skills, attitudes/values and allows continuous development" (Senac, 2015a). Therefore, part of the role of NCPs is to define the skills that students are expected to develop throughout each course. In NCPs, each competency is a CCU, which, in turn, is presented as a set of descriptors (knowledge, skills, and attitudes/values). In addition to these elements, each CCU has a set of indicators (CCI) to define the development of the CCU, and we use them as the basis for analysing the impact of automation. Figure 1 illustrates this structure for the Gastronomy Technician course as an example.

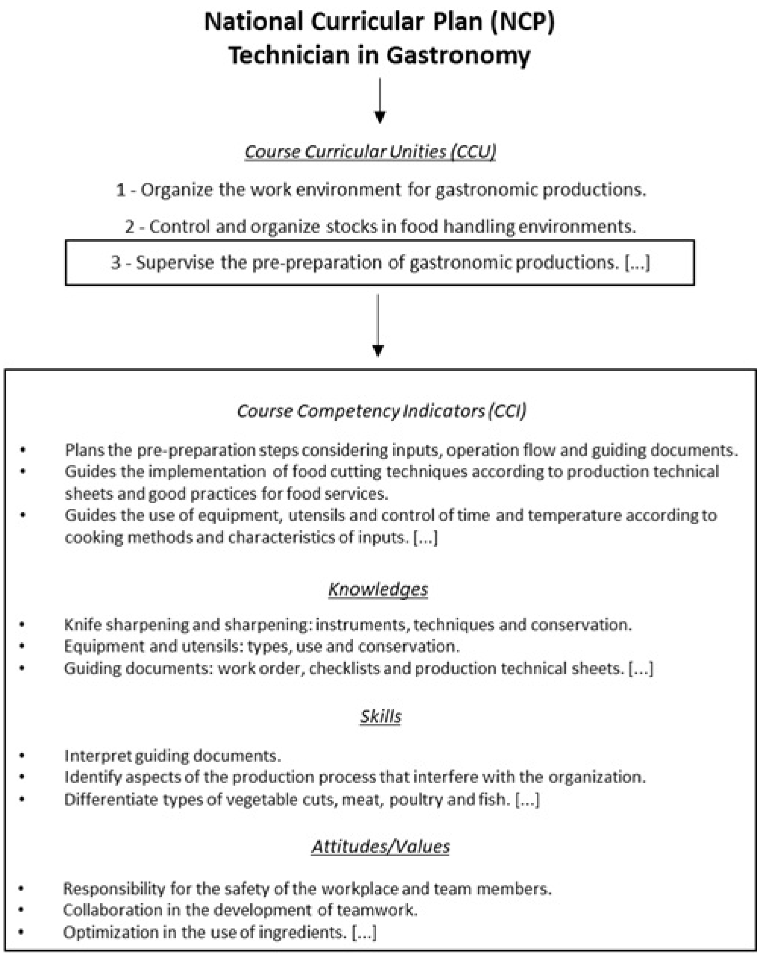

Figure 1: Structure and Components of the Senac National Curricular Plan, Illustrated With the Gastronomy Technician Course (Course Curricular Unities, Indicators, Knowledges, Skills and Attitudes/Values; Senac, 2015a)

The institution offers technical courses divided into fifteen segments: Arts, Commerce, Design, Educational, Events, Games, Gastronomy, Management, Environment, Cultural Production and Design, Health, Security, Information Technology (IT), Tourism, Hospitality and Leisure. The final database is composed of 2,100 CCIs related to 403 CCUs and 35 courses (Table 1).

Table 1: List of Technical Courses Included in the Automation Impact Analysis by Technological Axis and Segment

Technological Axis	*Segment*	*Technical Course*
Environment and Health	Environment	Environmental
	Health	Clinical Analysis
		Nursing
		Aesthetics
		Pharmacy
		Massage Therapy
		Nutrition and Dietetics
		Optical
		Podiatry
		Dental Prosthesis
		Radiology
		Oral Health
Educational and Social Development	Educational	School Secretariat
Management and Business	Commerce	Real Estate Transactions
	Management	Administration
		Foreign Trade
		Accounting
		Finance
		Logistics
		Human Resources
		Secretarial
Information and Communication	Games	Digital Games Programmer
	IT	Computer Graphics
		Computer
		IT for Internet
		IT and IT Support
		Computer Network
Cultural Production and Design	Art	Photographic Process
		Theater
	Design	Interior Design
		Fashion Production
Security	Security	Occupational Safety
Tourism, Hospitality and Leisure	Events	Events
	Gastronomy	Gastronomy
	Tourism	Tour Guide

3.2 Assessing the Impact of Automation

We implemented a three-stage methodology to estimate the impact of automation on technical courses: i) Technological mapping; ii) prompt development; iii) assessment. The methodology is summarised in Figure 2 and described in the upcoming sections:

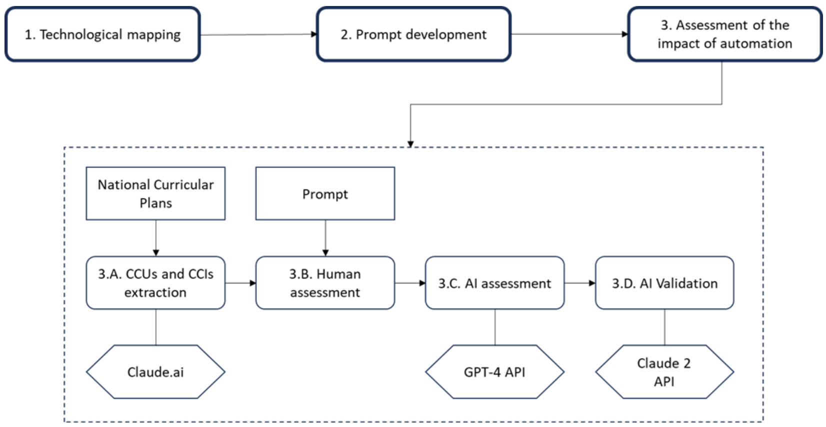

Figure 2: Illustrative Diagram With an Overview of the Research Methodology Applied in the Study

3.2.1 Technological Mapping

This stage consisted of mapping categories of automation technologies related to the fifteen economic segments for which Senac offers technical courses. The mapping aimed to find the current state of the art of automation technologies (without considering expectations of medium or long-term). We consulted both academic and grey literature (technical reports, *whitepapers*, etc). Given the perceived speed of technological advancement, the search for sources only considered publications from the last two years.

3.2.2 Prompt Development

The rubric is a set of instructions that must be followed by whoever carries out the assessment. Here, it is primarily based on the work conducted by Eloundou et al. (2024) and Gmyrek et al. (2023). Documenting the rubric is essential to guarantee that the work carried out in the research can be understood, validated, and replicated by other researchers. Then, an adapted rubric version was used as a prompt in the GPT-4 API to perform the AI assessment.

It was an iterative process in which each new text version was tested in ChatGPT for refinement according to the assertiveness and quality of the response received. This was done over 30 times during the writing stage alone, with the rubric in its prompt format being further refined during the AI assessment process. As the impact of automation was evaluated based on seven categories of technologies, not just LLMs, the rubric considers that the evaluator needs to inform not only the degree of automation but also which category of technology and specific technology would be used, in addition to justifying this decision. The final version of the rubric contains five pages of text and is presented as supplementary material.

3.2.3 Automation Impact Assessment

Finally, assessing the impact of automation on technical courses has an important feature: the interaction between the researchers and the AI. First, the researchers evaluated the CCIs of 6 courses from different technological axes: Administration Technician, Nursing Technician, Computer Technician, Interior Design Technician, Occupational Safety Technician, and Gastronomy Technician. This analysis aimed to test and improve the rubric and create a base of examples to include in the GPT-4 prompt.

Then, we sent the prompt to the GPT-4 API through a Python code that extracted a certain number of rows from the CCI spreadsheet containing, each one, a unique identifier (id), the name of the course, and the CCUs and CCIs to be evaluated. The prompt was modified several times until we got an improved version that provided satisfactory answers based on the researchers' evaluation (Step 3B in Figure 2). The complete list of CCIs was evaluated in two equal parts to test and refine it. Then, manual quality tests were carried out with 101 CCIs, randomly selected. Each answer could be classified as: correct (no adjustments needed); partially correct (divergence between the AI and the human assessment, but not necessarily a wrong answer due to the subjectivity inherent to the activity carried out); or incorrect (unsatisfactory answer in one or more fields).

The results of each round of evaluation are presented in Table 1. From the first to the second evaluation, the percentage of results considered correct went from 71% to 81%, and the number of errors (cases in which a column was not filled in or information from one column was found in another) went from 4% to 0%. As no change was noticed in the number of results considered incorrect (10%, in both cases), an additional step was included in the methodology to guarantee the quality of the results.

Table 2: GPT-4 API Test Results With the Automation Impact Assessment Prompt

Test results evaluation	1st test	2nd test
Correct	72 (71%)	82 (81%)
Partially Correct	15 (15%)	9 (9%)
Incorrect	10 (10%)	10 (10%)
Error	4 (4%)	0
Total	101	101

Step 3.D (Figure 2) was the final stage of the methodology aimed at dealing with the 10% rate of incorrect results that did not change even with the improvement of the prompt. As this was mainly due to limitations of the OpenAI model itself (such as hallucinations), we applied the same methodology to other LLM models (Anthropic's Claude 2) to verify the answers given by GPT-4. The prompt for Claude 2 (Annex A) presented the task previously requested for GPT-4. In cases where GPT-4's response was considered incorrect, Claude 2 was asked to justify its evaluation. This occurred for 522 cases of the 2,100 ICs evaluated. These cases were manually consolidated into a final spreadsheet.

4 Results

The results of the main steps of the research methodology are divided into the next two subsections: Technological mapping (4.1) and assessment of the impact of automation (4.2).

4.1 Technological Mapping

The first set of results regards identifying the categories of technologies to be considered in evaluating the impact of automation on the segments served by the technical courses offered by Senac. The search for references resulted in three technical reports (Future Today Institute, 2023; McKinsey & Company, 2022; World Economic Forum, 2023) and two peer-reviewed papers (Taherdoost, 2022; Sigov et al., 2022). The mapping resulted in a list of technologies divided into two groups: Enabling Technologies and Automation Technologies.

Enabling Technologies provides the crucial infrastructure and protocols needed to enable or power large-scale digitalisation (the foundation upon which Automation Technologies are built and operated). The impact of enabling technologies is felt across virtually every industry, from logistics and finance to healthcare and entertainment, enabling new transaction, collaboration, and interaction methods. In this research, the enabling technologies identified for the segments served by Senac's technical courses are Biotechnology, Blockchain, Cloud and Edge Computing, Advanced Connectivity, Nanotechnology, and Web 3.

Automation technologies – the focus of this research – represent a diverse set of tools and approaches that are actively reshaping how people work, and organisations operate and interact with their customers. Playing a crucial role in redefining the limits of what is possible, these technologies drive a paradigm shift in operational efficiency, customer engagement, product development, and business model innovation. We identified seven main automation technologies described below: i) 3D/4D printing and modelling; ii) Applied AI; iii) Data analytics; iv) Digital Platforms and Applications; v) Extended Reality; vi) IoT and Connected Devices; vii) Robots.

4.1.1 3D/4D Printing and Modelling (IMP)

3D/4D printing and modelling (IMP) is an additive manufacturing technology that involves building a three-dimensional object, layer by layer, from a digital file. In 3D printing, materials like plastic, metal, or ceramic are deposited or fused to form a 3D object. 4D printing takes this a step further, allowing the creation of objects that change shape or function after printing under the influence of specific environmental conditions such as heat, light, or humidity. These technologies transform production and manufacturing across multiple sectors, including healthcare, construction, and fashion.

4.1.2 Applied Artificial Intelligence (AAI)

Applied Artificial Intelligence (AAI) involves using AI techniques and tools in practical and concrete applications. This technology is underpinned by a variety of subfields, such as machine learning (where computers are programmed to learn from data), natural language processing (which allows computers to understand and respond to human language), and computer vision (where computers are trained to interpret and understand the visual world). AAI can be used to improve processes, increase efficiency, reduce human error, and generate valuable insights across a wide range of industries.

4.1.3 Data Analytics (DA)

Data Analytics (DA) is the process of inspecting, cleaning, transforming, and modelling data to discover useful information, formulate conclusions, and support decision-making. It is a set of techniques and methodologies that range from the collection and storage of raw data to its interpretation to obtain valuable insights. DA can be applied in many different contexts, from scientific research to business and management, and can include different types of analytics, such as descriptive, diagnostic, predictive, and prescriptive analytics.

4.1.4 Digital Platforms and Applications (APP)

Digital platforms and applications (APP) are software solutions and services that enable digital content creation, sharing, and manipulation. They can range from social media apps and video streaming platforms to graphic design software and content management systems. These digital tools enable communication, collaboration, creativity, and productivity on an unprecedented scale and profoundly impact almost every aspect of modern life, including work, education, entertainment, and art.

4.1.5 Extended Reality (ER)

Extended Reality (ER) represents the combination of one or more technologies that allow the creation of experiences that merge with real and virtual worlds. ER can include: Augmented Reality (AR) that interacts directly with and overlays external reality (for example, AR glasses with live translation), functioning interactively in 3D and in real-time; Virtual Reality (VR), which replaces the real world (for example, through VR glasses) by placing the user in a wholly digital experience that uses external cameras/sensors to render movements in virtual worlds; Mixed Reality (MR) which modifies the real world through a device, expanding or reducing a user's view of the world.

4.1.6 IoT and Connected Devices (IOT)

The Internet of Things (IOT) and connected devices refers to an ecosystem of physical devices, vehicles, appliances, and other items embedded with sensors, software, and connectivity to enable data exchange with other devices and systems over the Internet. They range from everyday household items like refrigerators and thermostats to complex devices like drones and industrial machines. IoT allows devices to be controlled remotely through networks of devices, creating opportunities for more direct integration between the physical world and digital systems.

4.1.7 Robots (RBT)

Robots (RBT) are advanced programmable machines capable of performing a series of tasks autonomously or semi-autonomously, integrated with sophisticated systems that allow them to perceive their environment, process information, and perform complex actions. They play crucial roles in modernising various sectors and stand out for enhancing efficiency and safety in daily operations. Humanoid robots mimic human characteristics and behaviours, facilitating intuitive interaction with people, while non-humanoid robots, varying in shape and size, are designed for specific tasks, often taking on dangerous or tedious roles for humans.

4.2 Assessing the Impact of Automation

After refining the rubric/prompt, a human evaluation was carried out on six courses (Administration Technician, Nursing Technician, Computer Technician, Interior Design Technician, Occupational Safety Technician, and Gastronomy Technician), one from each technological axis. For each CCI, we defined the level of automation, the categories of technologies and technologies that could be used to automate it, and a justification for the level of automation that described how each technology would be used.

In addition to testing and improving the rubric, the human assessment stage created a list of examples that were included in the prompt used in the next stage of AI assessment. Figure 3 illustrates the output from this process.

Course: Gastronomy Technician
CCU: Assist in the operational management of gastronomic enterprises
CCI: Organizes work schedules for the kitchen team considering labor legislation, organizational controls and the operational needs of the establishment

Automation level: Medium (40-60%)

Technology category: Digital Platforms and Applications **Technology:** Scheduling systems

Rationale: Scheduling systems can generate optimized work schedules, but manual adaptations based on unforeseen circumstances, legislation and human factors are still frequently necessary, requiring human supervision.

Course: Interior Design Technician
CCU: Prepare preliminary interior design study
CCI: Prepares interior layout proposal, according to drawing techniques, sketches and perspectives

Automation Level: None (0-10%)

Technology category: None **Technology:** None

Rationale: Requires a sense of space and creativity and is not very automatable.

Course: Computer Technician
CCU: Develop Algorithms
CCI: Develops computational algorithms according to the premises of the selected language

Automation level: High (70-80%)

Technology Category: Applied Artificial Intelligence **Technology:** Generative AI

Rationale: Software development is highly automatable with intelligent programming wizards and generative AI.

Figure 3: Examples of Human Assessment Results for Automation Impact (Gastronomy, Interior Design, and Computer Technician Courses)

Once the researchers personally assessed the expected impact of automation on a subset of technical courses, all 2,100 CCI were evaluated using the GPT-4 API. A review of all results was carried out using the Claude 2 API. In general, 821 CCIs (39.1%) are at a "Medium" level of automation impact, followed by 655 (31.2%) at the "Low" level and 273 (13.0 %) with no impact. On the other hand, 337 (16.0%) CCI are at the "High" level, and the "Total" level was associated with only 14 CCI (0.7%) (Figure 4).

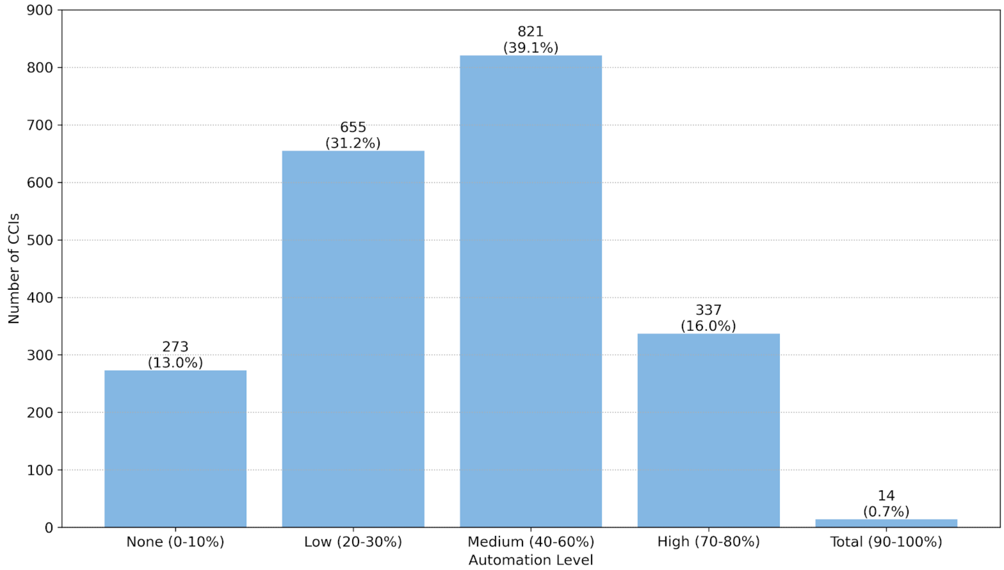

Figure 4: Distribution of CCIs According to the Assigned Automation Level (None, Low, Medium, High, and Total)

In Figure 5, it is possible to see that Digital Platform and Applications (APP) is the most cited technology to impact technical courses (1,141 occurrences), approximately three times more than the following categories, which has similar occurrences: Applied Artificial Intelligence (AAI), with 401 citations and Data Analysis (DA), with 400 citations. Among the least cited, we have 3D/4D Printing and Modeling (IMP) with 25 occurrences, and Extended Reality (ER) cited 40 times.

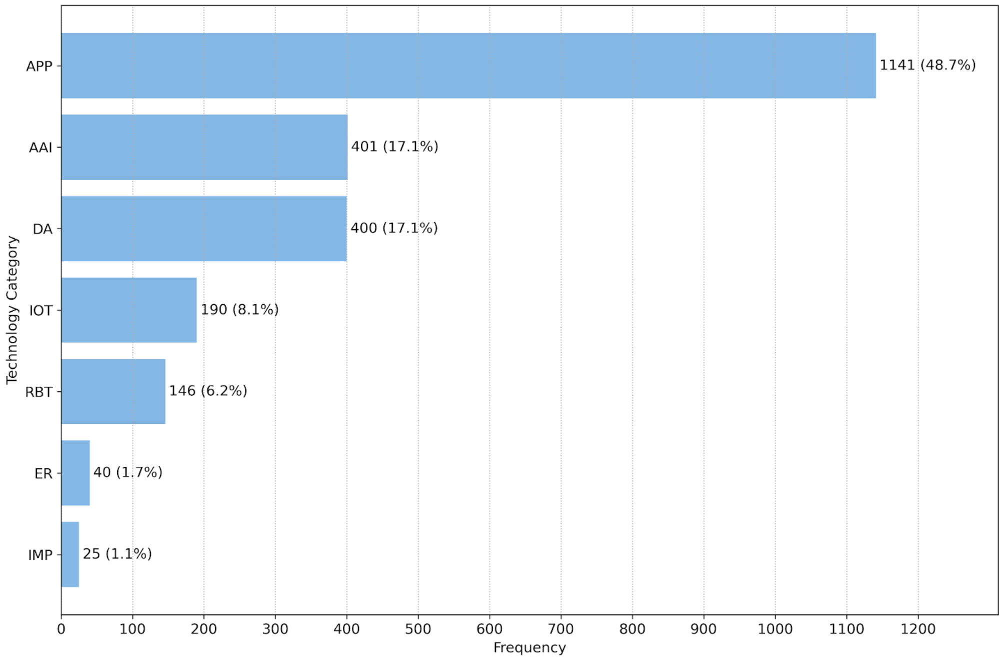

Figure 5: Frequency of Technology Cited as Impacting Technical Courses

Figure 6 shows the impact of automation on each course in Senac. Of the 35 technical courses the institution offers, 8 (23%) have at least 30% of their CCIs with a High or Total level of automation impact. On the other hand, 20 (57%) of the courses have up to 30% of their CCIs at the None or Low levels[2].

2 Full results of the distribution of CCIs in each automation level can be requested from the authors.

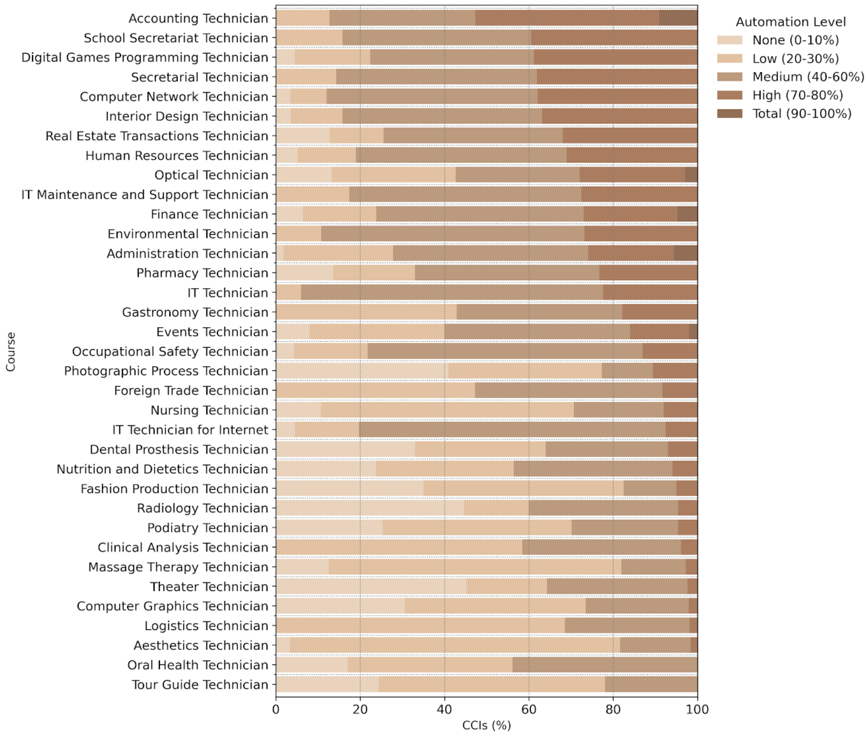

Figure 6: Distribution Of Automation Impact Levels Across Senac's Technical Courses

The analysis of the courses grouped by technological axis shows that the "Educational and Social Development" axis, which only has the School Secretariat Technician course, has the most significant predicted impact. The "Management and Business" and "Information and Communication" axes have more courses. In both axes, we have a combination of courses with more significant impact, such as Accounting Technician, and courses with little impact, such as Logistics Technician. Axis such as "Environment and Health" and "Tourism, Hospitality and Leisure" stand out for having a lower expected impact from automation, as shown in Figure 7.

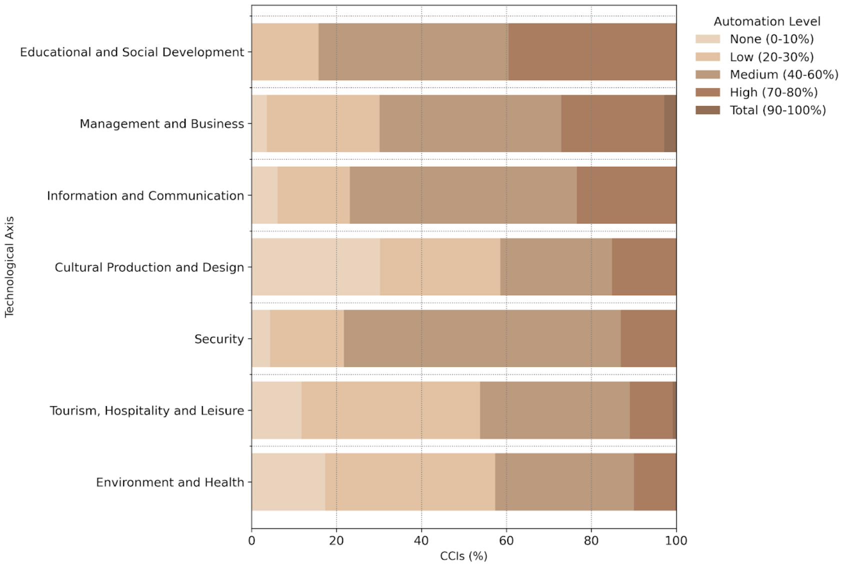

Figure 7: Distribution of Automation Level by Technological Axis

The cross between the number of occurrences of each technology category in the analysis of the impact of automation on each course, presented in the heat map in Figure 8, shows that the most cited technology category, Digital Platforms and Applications, has a high occurrence in a large variety of courses. At the same time, we observed where the least mentioned technologies (in blue) are applicable, such as 3D/4D Modeling and Printing in the Oral Health Technician course or Extended Reality in the Massage Therapy Technician course.

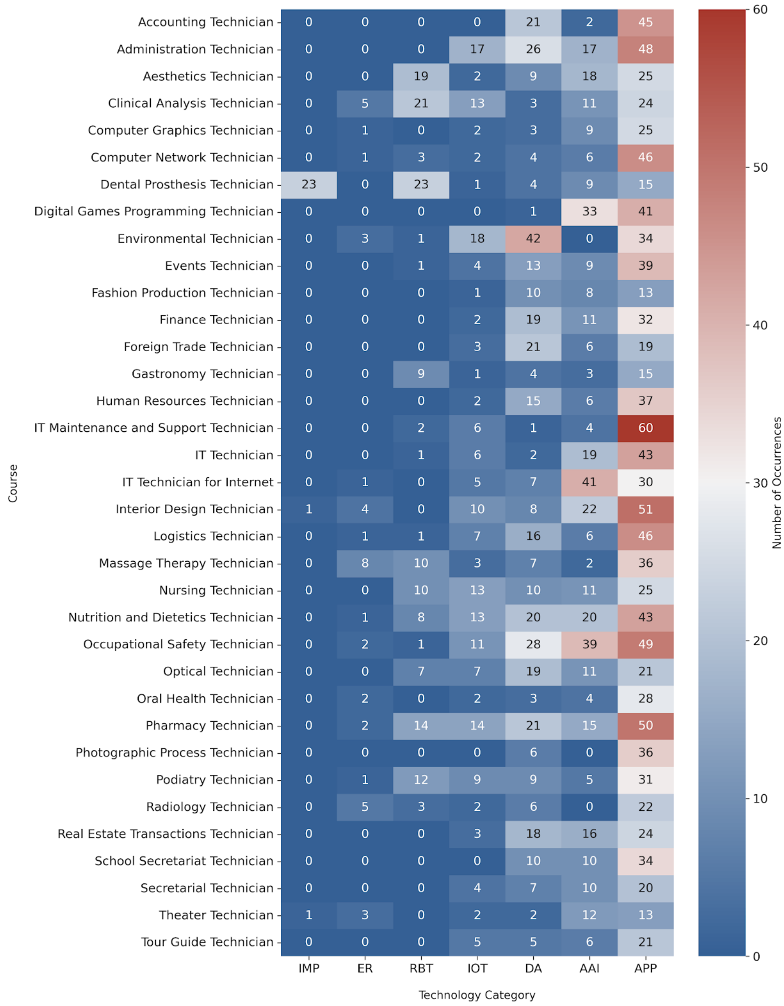

Figure 8: Heatmap of Technology Category Count Frequency by Coursetable

5 Discussion

Unlike previous research on the impact of automation on the labour market (Chen et al., 2023; Eisfeldt et al., 2023; Eloundou et al., 2023; Gmyrek et al., 2023), our research specifically focused on the impact on VET education, more specifically, technical education. This specific approach revealed that the majority (70.3%) of the CCIs of Senac's technical courses are at Medium (39.1%) or Low (31.2%) levels of automation impact, which suggests the currentness and relevance of the courses offered. This result contrasts with the common perception of rapid obsolescence of technical skills due to technological advancement. For this to remain true, it is critical to integrate emerging technologies into curricula to complement and expand students' skills rather than replace them. The lack of studies that analyse the impact of automation on education creates a challenge when discussing the results with similar research. In the absence of this direct comparison, a possible alternative is to compare the evaluation results of technical courses with the impact of automation predicted for occupations related to the courses analysed in the research.

Although direct studies on the impact of automation on vocational education remain scarce, there is a growing body of research that highlights how automation risk interacts with broader social and labor market dynamics. Cheng et al. (2021), for instance, show that workers in highly automatable occupations tend to face worse psychosocial working conditions, including lower job control, higher insecurity, and more work-related injuries. These findings suggest that automation risk is not only a technological or economic issue but also a social one, which reinforces the importance of vocational education in preparing individuals for more resilient and sustainable employment pathways. By aligning curricula with less automatable skillsets, VET can play a role in mitigating negative social outcomes associated with automation.

Moreover, task-based assessments of automation risk, such as those presented by Filippi and Trento (2023), emphasize the importance of non-routine cognitive and social skills in shaping future employability. Their findings reveal that occupations at lower risk of automation rely on attributes such as perception, manipulation, creative intelligence, and social intelligence — competences that can be nurtured within technical education, provided curricula are adapted accordingly. This further underlines the significance of updating VET programs not just to keep pace with technology, but to strategically enhance the human dimensions of work that remain less susceptible to automation. The National Catalog of Technical Courses (*Catálogo Nacional de Cursos Técnicos* or CNCT, in Portuguese) provides a set of definitions for technical courses offered in Brazil, including the professional profile of completion, minimum workload, training itineraries, and occupations from the Brazilian Classification of Occupations (CBO) related to each course (Ministério da Educação e Cultura, 2023). To obtain the probability of automation for each occupation, we used (Laboratório do Futuro, 2019; Lima et al., 2021) findings which adapted (Frey & Osborne, 2017) to the Brazilian context.

By calculating the average automation probability of occupations related to each course, it was possible to arrive at the automation probability estimates presented in Table 2. It is worth noting that this comparison is based on different methodologies, given that the research presented here analyses Senac's technical courses at a detailed level, while the assessment of the impact of automation takes place more broadly, observing skills and activities of some occupations. and then applying Machine Learning and Statistics techniques to expand the analysis to all occupations.

Table 2: Estimated Probability of Automation of Occupations Related to the Technical Courses Analysed (Laboratório do Futuro, 2019; Lima et al., 2021)

Course	P(Automation)
Low	
Computer Graphics Technician	4%
Digital Games Programming Technician	4%
Nursing Technician	9%
Nutrition and Dietetics Technician	13%
Radiology Technician	23%
Occupational Safety Technician	25%
Aesthetics Technician	29%
Average	
Events Technician	38%
IT Technician	43%
Clinical Analysis Technician	47%
IT Technician for Internet	48%
Fashion Production Technician	48%
Interior Design Technician	50%
Massage Therapy Technician	54%
Theater Technician	58%
Oral Health Technician	62%
High	
Optical Technician	71%
IT Maintenance and Support Technician	72%
Computer Network Technician	72%
Foreign Trade Technician	73%
Environmental Technician	77%
Tour Guide Technician	91%
Pharmacy Technician	92%
Human Resources Technician	93%
Real Estate Transactions Technician	94%
Gastronomy Technician	94%
Podiatry Technician	95%
Logistics Technician	95%
Administration Technician	96%
School Secretariat Technician	96%
Secretarial Technician	96%
Dental Prosthesis Technician	97%
Accounting Technician	98%
Finance Technician	98%

The results demonstrate that 18 (53%) of the 34 courses[3] analysed are in the range of high probability of automation (above 70%), 9 (26%) are in the medium range (between 30 and 70%) and 7 (21%) are in the low range (less than 30%). It is clear, then, that the distribution of the impact of automation of the CCIs of the analysed courses tends to be smaller than the probability of automation of the occupations linked to the courses. This result aligns with broader international evidence showing that occupations most at risk of automation often cluster in specific sectors or require routine tasks, as highlighted by Albuquerque et al. (2019) and Christenko (2022). However, despite the high estimated risk of automation, actual labor market transformations tend to be slower and mediated by factors such as occupational mobility and skill transferability. Christenko (2022) notes that workers in occupations sharing tasks with lower-risk roles can more easily transition in the face of job displacement, reinforcing the importance of technical courses that foster transferable competencies across sectors.

Besides analysing the impact of automation on technical courses, the research demonstrated the relevance of different technology categories for them. The results showed that Digital Platforms and Applications are predominant, reflecting current and future trends in the job market. This finding is consistent with related work that emphasises the rise of AI and digital tools. In contrast, 3D/4D Printing and Modeling proved to be less relevant, which may indicate a need to reevaluate the emphasis given to these technologies in courses.

Recent studies (Katz et al., 2023; Ramos et al., 2022) also suggest that automation does not uniformly reduce labor demand but instead reshapes it. While jobs with high automation risk are indeed vulnerable, occupations requiring digital competencies and higher education levels tend to grow. This dynamic is particularly relevant for VET, as it underscores the need for curricular strategies that prepare students not only to avoid displacement but also to access emerging job opportunities. Moreover, these studies warn of possible exclusion effects for low-skilled workers — underscoring the strategic role of technical education in promoting inclusive access to future-proof occupations.

The methodology used in this research, which combined qualitative and quantitative analyses using LLM models, stands out from traditional methods. This approach allowed for a quick and comprehensive assessment of CCIs, something that could not be done before the emergence of technologies such as ChatGPT, considering the volume of data analysed and the requirement for knowledge in different areas of professional activity. Furthermore, the modular nature of the proposed methodology enables other institutions to reproduce it easily, as elements such as the technology categories or curricular plans can be modified with minimal effort, while preserving the core of the developed prompt and code.

3 Photographic Process Technician course has no occupations listed in the CNCT and is left out of this comparison.

It is also important to mention that the use of LLMs as a central component of the methodology is conducted carefully and responsibly (Braga et al., 2024). During the implementation, we refine the prompts iteratively, test intermediate outputs to ensure robustness, and systematically review the results. Finally, since our outputs serve as one of the inputs for updating the NCPs, they undergo an additional review by professionals with expertise in education.

Given the accelerated pace of technological change, recommendations for VET institutions include constantly adapting NCPs and considering including emerging technologies identified in the curricula. Furthermore, identifying emerging automation technologies suggests opportunities for creating new professional qualification courses, meeting the requalification needs of graduates, and preparing them for recent technological advances.

Collaboration with companies and the establishment of strategic partnerships with technology companies are essential. These partnerships can facilitate the incorporation of updated knowledge and technologies into curricula and enable the introduction of more costly technologies, such as Robotics and Extended Reality, in classrooms.

6 Conclusion

The research on the impact of automation on Senac's technical courses presented here is an important effort to help align VET supply to labour market demands. Over the next years, we can expect to continue the accelerated advancement of the technologies that make up the 4th Industrial Revolution. Only in the area of Generative AI, between June and October 2023, the period in which we planned and carried out this research, major changes occur, such as ChatGPT gaining the ability to "see" images and interpret them; new LLM models were launched, such as the Mistral 7B; Adobe launched two new versions of Firefly, its platform for generating images from text; and Gamma, a platform that uses AI to help create presentations has been launched.

Due to this rapid technological change, the process of evaluating new technologies and adapting the Professional Education offered in any institution also needs to be accelerated. In this sense, the methodology developed and used in this research meets this speed requirement without compromising quality.

The AI evaluation process applied in this research makes it possible to deal with large volumes of information quickly. Running the evaluation process for 2,100 ICs was done in just 1 hour and 30 minutes. Furthermore, thinking about facilitating the process of running the research with other courses or categories of technologies, the process of evaluating the impact of automation, including reviewing the results, was designed in a modular way and in Python code, allowing for easy adaptation and reproduction in other contexts.

The research results demonstrate that 1,476 (70%) of the 2,100 ICs in Senac's technical courses are concentrated at Medium or Low levels of automation impact. This important result indicates that despite the great advances experienced in recent years, Senac was able to keep its courses up to date.

In terms of the most relevant technologies, "Digital Platforms and Applications", "Applied Artificial Intelligence", and "Data Analytics" stood out, with the first technology category being almost three times more cited than the second one. Due to the advances made in this area, we can expect that in the short term, we will see Applied AI grow in use in the most diverse areas.

One of the main limitations of this study lies in its focus on courses offered by Senac, restricting the analysis of results to the specific context of this institution. However, the methodology developed can be replicated for technical courses and other categories in other institutions. Therefore, there is an important possibility for research that involves analysing and comparing how the same course is impacted by automation in different institutions given the variability in terms of curricular plans. Future work could expand the research to include a wider variety of technical education institutions, providing a broader understanding of the impact of automation on vocational education in different contexts. This would help validate and refine the findings of this study and identify broader patterns and trends. Additionally, it would be beneficial to incorporate periodic assessments to monitor technological changes and their implications for technical courses, ensuring that data remains relevant and current.

Another limitation of the study is the dependence on emerging technologies such as GPT-4 and Claude 2 in the analysis of CCIs. As these are brand-new technologies, there may be implicit biases inherent to LLMs, potentially influencing the interpretation and classification of data. Furthermore, hallucination, which occurs when an LLM gives a wrong answer believing it to be correct, is known to exist in any model, including those used. In this sense, we mitigated this problem by analysing the results given by GPT-4 with Claude 2. Future work can run the methodology with a wider range of models and test which best responds to the proposed prompt.

When considering the state of the art of technologies another limitation arises. However, we understand that there is a considerable time between the emergence of a given technology and its introduction into company operations. Therefore, it was decided to explore the state of the art because this allows a more realistic and coherent analysis of the impact of automation to be made. Future work may consider other technology categories, including those not currently in such a high state of maturity. We are currently developing an updated version of the methodology that includes, among other improvements, partly allowed by new LLMs, a new variable to the evaluation called "adoption horizon" that allows for technology categories that are in different stages of development to be suggested.

An important aspect of future research is to study how automation affects non-technical skills, such as creativity and interpersonal skills, and how it changes students' expectations and experiences. Furthermore, exploring strategic partnerships with companies to assess the real needs of the job market and how educational institutions can adapt their curricula to meet these needs would be a significant step towards aligning technical education with the demands of the Fourth Industrial Revolution.

We hope that this work, mainly the methodology presented here, will be an important contribution to analysing the impact of automation on VET institutions and the consequent and necessary adaptation of course curricula, especially those most affected by emerging technologies. In this way, we will be able to train professionals who are fully equipped to deal with the impact of automation on their work and act as agents of economic advancement.

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Ethics Statement

The authors report there are no competing interests to declare.

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Biographical Notes

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Cicero Braga, Ph.D., is an Applied Economist and current Technical Advisor at the National Department of the Brazilian National Service for Commercial Education (SENAC). He holds a doctorate in Applied Economics from the Federal University of Viçosa (UFV), where he focused on labor markets, education, and inequality. His research explores the intersections between technological change, vocational education and training (VET), and the future of work in emerging economies. Braga has collaborated on studies involving big data and public policy evaluation, focusing on micro development, gender dynamics, and workforce relations.

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Appendix

Prompts

Extraction of CCUs and CCIs from NCPs via Claude.ai

In section 5.1 of the document, there are Curricular Units with a table below each one with a list of Indicators. I need you to extract the list of all Curricular Units and their respective Indicators. Generate a csv using ; as a separator with the following format:

column 1: course name
column 2: UC number (format: UCn)
column 3: name of the Curricular Unit
column 4: UC indicator number
column 5: name of the UC indicator

Evaluation of CCIs via GPT-4 API

Instructions:
Evaluate the impact of automation on the Competency Indicators (ic) of the Curricular Units (uc) of technical courses. Each course has a set of uc and each uc has a set of ic that are evidence of the development of the student's competence. Therefore, always consider that the course and the uc provide the context in which the ic should be evaluated. You will receive the name of a course and a list in the format [uc]_[ic].

Assumptions:

1. You are an expert in technology, work and professional education.

2. Only use the technology categories (cat_tec) listed. If there is no cat_tec to be associated with the IC, the niv_auto value of that IC must be '0'.

3. Consider that we are in 2023, trying to analyze the 'state of the art' of technologies, but your training base is from 2021. Therefore, consider two years of technological advancement more than you know.

4. Multiple cat_tec and technologies (tecs) can be used to automate the same activity, but you can only select up to three cat_tec per IC and only one tec. Therefore, always choose the most relevant technologies for each case. You can repeat the same cat_tec, as long as it has more than one tec associated with it.

5. Automation must be understood as the adoption of a technology to carry out an activity currently performed by a person and must always maintain or improve the quality and

execution time of the activity compared to those that a technical worker with intermediate experience would perform in Brazil would be able to deliver.

Response format:
.csv (divider ';'). Always start the response with the file headers on the first line and do not repeat these headers in the file: id;niv_auto;cat_tec1;tec1;cat_tec2;tec2;cat_tec3;tec3;justificationGPT. Ensure that each line of the answer has exactly 9 columns by filling in '0' in each field that has no information to be filled in.

The answer must have the following nine columns:

First column: Title: 'id'. Content: just the ID number given in the prompt;

Second column: Title: 'niv_auto'. Content: IC automation level (just the number);

Third column: Title: 'cat_tec1'. Content: first category of technology that would be used to automate the IC;

Fourth column: Title: 'tec1'. Content: first technology that would be used to automate the IC;

Fifth column: Title: 'cat_tec2'. Content: second category of technology that would be used to automate the IC;

Sixth column: Title: 'tec2'. Content: second technology that would be used to automate the IC;

Seventh column: Title: 'cat_tec3'. Content: third category of technology that would be used to automate the IC;

Eighth column: Title: 'tec3'. Content: second technology that would be used to automate the IC;

Ninth column: Title: ' justificationGPT'. Content: clear justification for the chosen level of automation and an explanation of how each of the selected technologies would be used to automate the IC.

Automation levels (niv_auto):
4 = Full (90-100%), 3 = High (70-80%), 2 = Medium (40-60%), 1 = Low (20-30%), 0 = None (0-10%)

Technology Categories (cat_tec):
AD = Data analysis: process of inspecting, cleaning, transforming and modeling data with the aim of discovering useful information, formulating conclusions and supporting decision making. It is a set of techniques and methodologies that range from the collection and storage of raw data to its interpretation to obtain valuable insights. Data analytics can be applied in many different contexts, from scientific research to business and management, and can include different types of analytics such as descriptive, diagnostic, predictive, and prescriptive analytics. Examples of technologies: BI Tools (Tableau and Power BI), Big Data Platforms (Hadoop and Spark) and Data Processing Libraries (Python and R).

AAI = Applied AI: involves the use of AI techniques and tools in practical and concrete applications. This technology is underpinned by a variety of subfields, such as machine learning, natural language processing, and computer vision. Applied AI can be used to improve processes, improve efficiency, reduce human error, and generate valuable insights across a wide range of industries. Examples of technologies: Generative AI (Dall-E and ChatGPT), Recommender systems (Netflix, Amazon) and RPA platforms integrated with AI (UiPath and Automation Anywhere).

IMP = 3D/4D printing and modeling: additive manufacturing technology that involves building a three-dimensional object, layer by layer, from a digital file. In 3D printing, materials such as plastic, metal or ceramic are deposited or fused to form a 3D object. 4D printing takes this a step further, allowing the creation of objects that change shape or function after printing under the influence of specific environmental conditions such as heat, light or humidity. Examples of technologies: Filament 3D printers (MakerBot and Ultimaker), 3D modeling software (AutoCAD and Blender) and 4D printing with intelligent materials that react to external stimuli.

IOT = IoT and Connected Devices: refers to an ecosystem of physical devices, vehicles, appliances and other items that are embedded with sensors, software and connectivity to allow the exchange of data with other devices and systems over the internet. They range from common household items like refrigerators and thermostats to complex devices like drones and industrial sensors. IoT allows devices to be controlled remotely through networks of devices, creating opportunities for more direct integration between the physical world and digital systems. Examples of technologies: Connected Inventory Management Systems (RFID and barcode), Telemetry and Occupational Health Monitoring (wearable devices) and Smart Building Management Systems (sensors and actuators).

APP = Digital Platforms and Applications: software solutions and services that allow the creation, sharing and manipulation of digital content. They can range from social media apps and video streaming platforms to graphic design software, content management systems, point of sale (POS) systems, online booking platforms and delivery apps. These digital tools enable communication, collaboration, creativity and productivity on an unprecedented scale.

Examples of technologies: Social media platforms (LinkedIn and Instagram), Productivity apps (Microsoft Office and Google Workspace), and Graphic design tools (Adobe Photoshop and Illustrator)

RE = Extended Reality: represents the meeting of one or more technologies that allow the creation of experiences that merge the real world and the virtual world and may include: Augmented Reality that directly interacts with and overlays external reality and works in a interactive in 3D and in real time; Virtual Reality that replaces the real world by placing the user in a completely digital experience that uses external cameras/sensors to render movements in virtual worlds; Mixed Reality that modifies the real world through a device, expanding or reducing a user's view of the world. Examples of technologies: Virtual Reality Devices (Oculus Rift and HTC Vive), Augmented Reality Applications (Pokemon GO and Apple's ARKit) and Mixed Reality Platforms (Microsoft HoloLens).

RBT = Robots: they are advanced programmable machines, capable of performing a series of tasks autonomously or semi-autonomously integrated with sophisticated systems that allow them to perceive their environment, process information and carry out complex actions. They play crucial roles in the modernization of various sectors and stand out for enhancing efficiency and safety in daily operations. Humanoids mimic human characteristics and behaviors, facilitating intuitive interaction with people, while non-humanoids, varying in shape and size, are designed for specific tasks, often taking on roles that are dangerous or tedious for humans. Examples of technologies: Social robots (Pepper and PARO), Delivery or surveillance drones (DJI and Amazon Prime Air) and Cleaning robots (Avibots Neo and Tennant T7AMR)

Example of CORRECT assessments:
7;Occupational Safety Technician_Perform assessment and control measures for physical, chemical and biological risks.;Identify and classify environmental risks, in accordance with technical literature, standards and applicable legislation.;2;AD;BI systems;RE;Augmented reality;0;0;Identification can be done through sensors and augmented reality while data analysis helps in classification.

21;Occupational Safety Technician_Perform investigation, recording and control of incidents, work accidents and occupational diseases.;Analyzes the incident and/or accident, according to technical procedures.;3;AAI;Chatbots;0;0;0;0;Involves analyzing data about the incident and making decisions based on previously established protocols. Human analysis remains important to review automated analysis, but applications and applied AI can help with data collection, such as a chatbot that follows the data collection methodology of the parties involved.

149;Nursing Technician_Perform prevention, promotion, protection, rehabilitation and health recovery actions.;Assists the client by measuring and monitoring vital signs, anthropometric measurements and blood glucose, according to health programs.;2;IOT;Smartwatches and devices/ health sensors;0;0;0;0;Connected devices can help with patient monitoring

197;NursingTechnician_Administerhigh-alertmedicationsandbloodcomponents.;Selects materials and supplies for administering high-alert medications and blood components, considering the client's characteristics and medical prescription.;0;IOT;Smartwatches and devices/ health sensors;APP;medical protocol systems;0;0;Involves consulting protocols and making decisions based on data, which can be assisted by devices for collecting information about the patient that can be used in decision making supported by protocol systems.

1044;Administration Technician_Assist the execution of actions relevant to the material and asset management processes in organizations_Classifies, organizes and labels assets, materials and products, in accordance with the organization's control standards and procedures.;1;IOT;Labels RFID;IOT;Monitoring and tracking devices;0;0;Classifying, organizing and labeling assets, materials and products can be facilitated by RFID, although the decision about which items to send where may still require some level of human intervention.

1054;Administration Technician_Assist in carrying out actions relevant to financial processes in organizations_Controls, organizes and classifies accounting payments and receipts, according to the current chart of accounts, sending tax documents to accounting.;3;APP;Systems accounting;APP;Process management systems;0;0;Control and communication flows with other internal and external areas can be automated via process management systems while accounting systems manage financial processes.

1480;Computer Technician_Plan and execute computer maintenance_Plans and organizes the use of resources according to the needs of customer demand and the work environment.;3;APP;Maintenance management systems;0;0;0;0;Management systems Maintenance services can help you plan and organize computer maintenance.

1507;Computer Technician_Develop Algorithms;Develops computational algorithms according to the premises of the selected language.;3;AAI;Generative AI;0;0;0;0;Software development is highly automatable with intelligent programming assistants and generative AI .

1791;Interior Design Technician_Structuring interior design project conception_Performs conceptual and stylistic study, according to the client's needs.;2;APP;Chatbot;AAI;G enerative AI;0;0;A chatbot can help collect information in a simple and friendly way and a generative AI can analyze this information and that about the environment to propose styles and sectorization.

1795;Interior Design Technician_Prepare preliminary interior design study_Prepare interior layout proposal, according to drawing techniques, sketches and perspectives.;0;0;0;0;0;0;0;Requires a sense of space and creativity and is not very automatable.

2055;Gastronomy Technician_Prepare gastronomic productions for the hot kitchen_Performs gastronomic techniques in hot kitchen productions in accordance with operational technical sheets and good practices for food services.;2;RBT;Culinary robots;0;0;0;0;Some robots Culinary professionals can already deal with relatively organized environments.

2070;Gastronomy Technician_Assistant in the operational management of gastronomic enterprises_Organizes work schedules for the kitchen team considering labor legislation, organizational controls and the operational needs of the establishment.;2;APP;Scheduling systems;0;0;0;0;scheduling can generate optimized work schedules, but manual adaptations based on unforeseen circumstances, legislation and human factors are still frequently necessary, requiring human supervision.

Examples of WRONG assessments:
665;Optical Technician_Prepare technical reports on optical products_Examines glasses, based on their physical state;2;AAI;AI tools for analysis;0;0;0;0;AI and data analysis can help in evaluation, but human experience is necessary in interpretation and final decision-making. (ERROR: niv_auto should be 0 or 1 because there are no technologies ready to check the physical state of glasses)

606;Nutrition and Dietetics Technician_Assist in the development of food products and the corresponding marketing strategies_Guides and monitors the hygiene of the food product development environment, in accordance with current legislation.;2;APP;Digital checklist systems;0;0;0;0;Guidance and monitoring of hygiene can be assisted by digital checklists, but execution still requires human action. (ERROR: does not consider applied AI and IoT and connected devices like cat_tec important for CI)

595;Nutrition and Dietetics Technician_Monitoring and guiding the implementation of diets for clinical and surgical patients_Performs hygiene and personal presentation procedures, in accordance with legislation and the SOPs of the Food and Nutrition Unit.;1;APP;Hygiene control software;0;0;0;0;Hygiene procedures are still best managed by humans, but can be aided by hygiene control software. (ERROR: considers a technology that does not exist: hygienic control software)

Take a deep breath and think step by step.

Claude 2 API assessment review
The attached prompt was sent to the GPT-4 API which gave the responses below (format: id;curso;uc_ic;niv_auto;cat_tec1;tec1;cat_tec2;tec2;cat_tec3;tec3;justificationGPT). Your job is to evaluate the answers given by GPT-4 considering how correct the level of automation given, the technology categories and technologies selected and the description offered are. For cases where any of the above items are considered incorrect, rewrite the response given by GPT-4 for that line following the instructions in the attached prompt.txt. In addition to the columns populated by GPT-4, include your justification for the assessment you made. Your response should be a .csv using ';' as a divider with the following TEN columns: id; niv_auto; cat_tec1; tec1; cat_tec2; tec2; cat_tec3; tec3; justificationGPT; justificationClaude.

Return ONLY this .csv in your answer, updating the lines that were wrong and repeating the correct lines as they were given in the prompt in the same order as the ids. Do not put the header in the .csv. Take a deep breath and think step by step, analyzing each of the ids sent in the prompt.