Analysis of automation and retraining opportunities for the Brazilian federal public service

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Abstract. *Context*: The speed of technological advancement has raised concerns about the impact of automation on work. Previous studies have analyzed this impact on the private sector, but there is little research focused on the Brazilian public sector, which faces additional challenges in dealing with this issue. *Objective*: To estimate the impact of automation on intermediate-level federal public positions and indicate professional retraining paths for civil servants, in the face of technological changes. *Methodology*: A 4-step approach was used, involving (1) mapping of automation technologies, (2) extraction and review of the job duties of 142 intermediate-level public positions from a government document with the support of AI models, (3) assessment of the importance level and horizon of automation of each job duty by GPT-4 Turbo and (4) suggestion of professional retraining courses for each position. *Results*: A considerable potential for automation of the analysed positions was identified, with 72% of the job duties with different automation levels in an immediate or short-term impact horizon. However, also considering the frequency and importance of each job duty, a considerable part of the positions had an impact between 0.10-0.28 points on a scale of 0 to 1. The technologies with the most occurrences in the analysis of automation impact were Machine Learning, Smart Sensors and Process Digitization Systems. In the end, 236 professional retraining courses were suggested to better prepare employees for possible technological impacts.

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1. Introduction

The speed at which new technologies are created and disseminated has increased over time (Comin & Hobijn, 2010). In the current 4th Industrial Revolution, we have ChatGPT as a recent example of technological diffusion that occurred at an unprecedented speed. In just 5 days, ChatGPT already had more than 1 million users and, in just two months, more than 100 million monthly active users (Reuters, 2023).

Such a fast pace of advancement brings a series of concerns to any organization from a work perspective. The rapid implementation of new technologies requires preparation on the part of employers, government and workers, which, if not done, can lead to problems such as technological unemployment (Lima, Barbosa, et al., 2021). It is important to emphasize that the impacts of these new technologies may affect different population groups in distinct ways, with women and black individuals potentially being the most disadvantaged due to their weaker labor market inclusion.

Over the past decade, a significant amount of research has been devoted to exploring the impact of automation on labor. Despite the volume of articles discussing the risk of unemployment caused by automation, there was no research that considered the distinction between the public and private sectors until 2021 (Adamczyk et al., 2021). As far as the search that was carried out for this research, there are only two articles have focused on the impact of automation on the Brazilian public sector (Adamczyk et al., 2021; De Oliveira Teixeira et al., 2022). Notably, the public sector does not have the flexibility that the private sector has to deal with the impacts of automation in terms of hiring, firing, and reallocating workers (Adamczyk et al., 2021; Banco Interamericano de Desenvolvimento, 2020).

This research aims to provide a new and updated estimate of the impact of automation on public sector occupations—an effort made necessary by the current pace of technological innovation and diffusion. It also seeks to go beyond previous studies by identifying professional retraining pathways that can help federal public servants modernize their work activities. The study was conducted over the course of a four-month postdoctoral project in partnership with the Secretariat for People Management of the Ministry of Management and Innovation in Public Services. The analysis presented here is part of a broader set of initiatives led by the Ministry to deliver data-driven insights for decision-making related to the creation, merging, elimination, or enhancement of hundreds of public service careers, as well as the planning and scale of future civil service entrance examinations.

The methodology developed to achieve this goal begins by identifying the main categories of automation technologies expected to impact work in the Brazilian public sector in the coming years. It then involves the use of Claude (a generative AI model similar to ChatGPT) to extract and review the job duties of selected positions. Based on these duties, GPT-4 Turbo—the latest model from OpenAI, the developer of ChatGPT—is employed to assess the potential impact of automation on each position and to recommend professional retraining courses aligned with the required technological updates. While the use of large language models (LLMs) for research purposes is still relatively new and presents several challenges, every step of this study was carefully designed and reviewed by both the research team and the public servants supervising the project. Moreover, the results are presented with appropriate caution, and their application will be subject to human validation and complemented by other methodologies and data sources.

The remainder of this paper is organized as follows. Section 2 presents other research related to the topic of automation, particularly those related to the object of this research, automation in the public sector, and the methodology for assessing the impact of automation. Section 3 presents the methodology of the work in its four stages and highlights important differences between the present study and previous ones. Section 4 has four parts, one for each stage of the methodology, and presents the categories of technologies found during the technological mapping, the result of the extraction and review of the job duties of the selected public positions, the results of the assessment of the impact of automation on the positions and the results of the process of proposing professional retraining courses in view of the identified impact. Section 5 concludes the paper by bringing some final remarks, limitations of the work and perspectives for future work

2. Literature review

The analysis of the impact of automation gained traction in 2013, when the seminal article by Frey and Osborne was published, still as a preprint, assessing how susceptible jobs in the US were to computerization[1] (Frey & Osborne, 2017b). Since then, the article has received more than 13,000 citations and has been applied in the context of several countries around the world (Brookfield Institute, 2016; Deloitte, 2015a, 2015b; Santos et al., 2015; World Bank Group, 2016), including Brazil itself. In the Brazilian case, 60% of the workforce would have a high probability of being automated, and the same correlation between level of education and the impact of automation was observed, with the correlation between wages and the impact of automation existing, but weak (Lima, Strauch, et al., 2021).

Specifically on the impact of automation on Brazilian public sector employees and their occupations, there are two recent studies that should be mentioned (Adamczyk et al., 2021; De Oliveira Teixeira et al., 2022). The first of these studies was carried out in 2021 by researchers from PUC-RS, ENAP, IDP-DF and CNPq and had as its object of analysis federal government employees (Adamczyk et al., 2021). In this study, the Bartik Occupational Tasks (BOT) method was applied, which involves separating the differential effects of automation from the national and structural effects that lead to local employment growth, and then analyzing the frequency of words in the activities of the occupations associated with the differential effects of automation. Natural Language Processing and Machine Learning algorithms were used to extract quantitative information from the descriptions of work activities in the Brazilian Classification of Occupations (CBO). In total, 521,701 public servants distributed across 389 positions were analyzed. As a result, this first study showed that 20% of federal public servants are in occupations that are highly susceptible to automation in the next decade. Here again, it was observed that occupations related to lower levels of education and lower wage levels are more representative among those with a greater chance of being automated.

The second study was conducted in 2022 by researchers from BIOTIC and IDP, and analyzed the public sector of the Federal District (De Oliveira Teixeira et al., 2022). The methodology adopted in this study was based on another study by researchers from IPEA that considered the importance and relevance of the activities performed by each occupation (according to the O*NET occupation database in the USA) by analyzing the frequency of words related or not to automation (Kubota & Maciente, 2019). Based on the results of this study, a correlation was made between

[1]Computerization, according to the authors, would be the automation caused by Computing technologies, in particular, Machine Learning and Mobile Robotics.

the positions and duties of the executive branch of the Federal District Government and the occupations analyzed by IPEA researchers to arrive at an estimate of the impact of automation on the public servants analyzed. As a result, of the almost 100,000 civil servants who occupied the 368 positions analyzed, 5.5% were at high risk of automation, 24.1% at medium risk, and 70.4% at low risk (Kubota & Maciente, 2019). In this study, the positions that required a lower level of education were also those with the highest risk of automation.

The launch of ChatGPT by OpenAI in November 2022 and its use by more than 100 million active users as of January 2023, a record (Reuters, 2023), has made AI a versatile and user-friendly tool for workers in a wide range of sectors. The potential of this technology to impact work has led to a new wave of research on the impact of Generative AI (Chui et al., 2023; Eisfeldt et al., 2023; Eloundou et al., 2023; Gmyrek et al., 2023; Noy & Zhang, 2023), the technology category to which ChatGPT belongs. Some of this new research has brought with it an important innovation to automation studies, which is the use of Generative AI itself in the impact assessment process (Eloundou et al., 2023; Gmyrek et al., 2023).

In the first study published using this methodology, researchers from OpenAI itself analyzed the impact that technologies such as Generative Pre-trained Transformers (GPTs), that is behind ChatGPT, would have on the US workforce. The authors prompted GPT-4 to evaluate a set of occupations based on the descriptions of their activities according to the degree of exposure to GPTs at three levels: E0, in case of no exposure or worsening of the result in case of adoption of the technology; E1, direct exposure, when ChatGPT would reduce the execution time of the activity by 50%; and E3, when access to ChatGPT was not enough, but software developed based on GPTs were able to reduce the execution time of the activity by 50%. As a result, the authors paper that 80% of the US workforce would have at least 10% of their activities impacted by GPTs, while 19% of the workforce would have at least 50% of their activities impacted by this technology. An important result that contrasts with the aforementioned research, carried out before the emergence of ChatGPT, is that the effects of GPTs span all salary levels, with higher-paying jobs potentially facing greater exposure (Eloundou et al., 2023).

It is worth noting that the impacts analyzed by the studies cited do not cancel out those found in studies from the last 10 years, but rather add to the previous ones. Thus, it is becoming increasingly difficult to identify any occupation or economic sector that is immune to the impact of automation technologies of the current 4th Industrial Revolution.

Another important recent study that used ChatGPT was the one carried out by the International Labour Organization (ILO), which also sought to understand the impact of GPTs on employment, in this case, at a global level. The authors used the International Uniform Classification of Occupations (ISCO-08) as a basis to analyze the 436 occupations described therein. Before assessing the impact of GPTs themselves, the authors asked GPT-4 to generate a definition and list of 10 activities for each of the occupations and ISCO-08 codes provided. Based on this list of activities and occupations, the authors proceeded to ask GPT-4 to evaluate each one on a range from 0 to 1 according to the degree of automation of the tasks if GPT were adopted (Gmyrek et al., 2023).

In the study presented, it is identified that five categories of tasks are significantly impacted, with an impact greater than 0.75: administration and communication, customer service, data and records management and maintenance, information processing, and language and information provision services. It was found that, among the occupational groups, the "Administrative and Office Support" sector is the most affected, with 24% of tasks highly susceptible to automation and 58% with medium susceptibility. In comparison, in other occupational groups, the proportion of highly vulnerable tasks varies from 1% to 4%, and those with medium exposure do not exceed 25%. Finally, the influence of automation on employment differs significantly between countries of different income levels, due to their distinct occupational structures. In low-income nations, only 0.4% of total employment is at risk of automation, while in high-income countries, this number increases to 5.5% (Gmyrek et al., 2023).

In addition to these international studies, research conducted in Brazil provides further insight into the potential impact of automation on the country's labor market. Kubota and Maciente (2019) analyzed the susceptibility of occupations in the formal sector to automation, utilizing a methodology that classified jobs based on the degree of automatability of their tasks. Their findings indicate that 56.6% of formal employment in Brazil consists of occupations with a high or medium-high percentage of automatable tasks. This study also highlights that while some occupations traditionally considered at risk, such as bank tellers and telephone operators, have seen employment decline, others with high automation potential—such as administrative roles—continue to grow. This suggests that the diffusion of new technologies may impact not only declining occupations but also those that have played a significant role in recent job creation.

Furthermore, the study underscores the regional and sectoral differences in automation susceptibility. Urban centers, particularly metropolitan regions, tend to have a lower share of highly automatable occupations (around 36% of formal employment), whereas smaller and more economically isolated municipalities exhibit a higher concentration of automatable jobs, particularly in transportation and logistics. From a sectoral perspective, the highest risks are observed in industries such as textiles, food production, wood processing, and metallurgy, as well as in certain service sectors like accounting, cleaning services, and logistics. This reinforces the need for policy interventions aimed at workforce reskilling and adaptation, especially in sectors and regions most vulnerable to automation-driven labor displacement.

In order to contribute to this field of research and provide data to support public policies, this research aims to analyze the impact of automation on a set of positions in the Brazilian public sector, as has been done before (Adamczyk et al., 2021; De Oliveira Teixeira et al., 2022), but using technologies such as ChatGPT, like more recent research on the subject (Eloundou et al., 2023; Gmyrek et al., 2023). In addition to defining automation levels for each position, the research presented here also seeks to indicate professional retraining paths for the positions analyzed. Further details on the methodological differences between this work and previous ones will be provided in the next Section on methodology.

3. Methodology

In order to estimate the impact of automation on public positions and indicate professional retraining courses, the methodology presented in Figure 1 was developed and used in this research. Each of these steps generated a product that can be considered a contribution of this research to the academic community and to Brazilian public management[2]. The methodology made extensive use of the most advanced and capable LLM models available at the time of execution of each step..

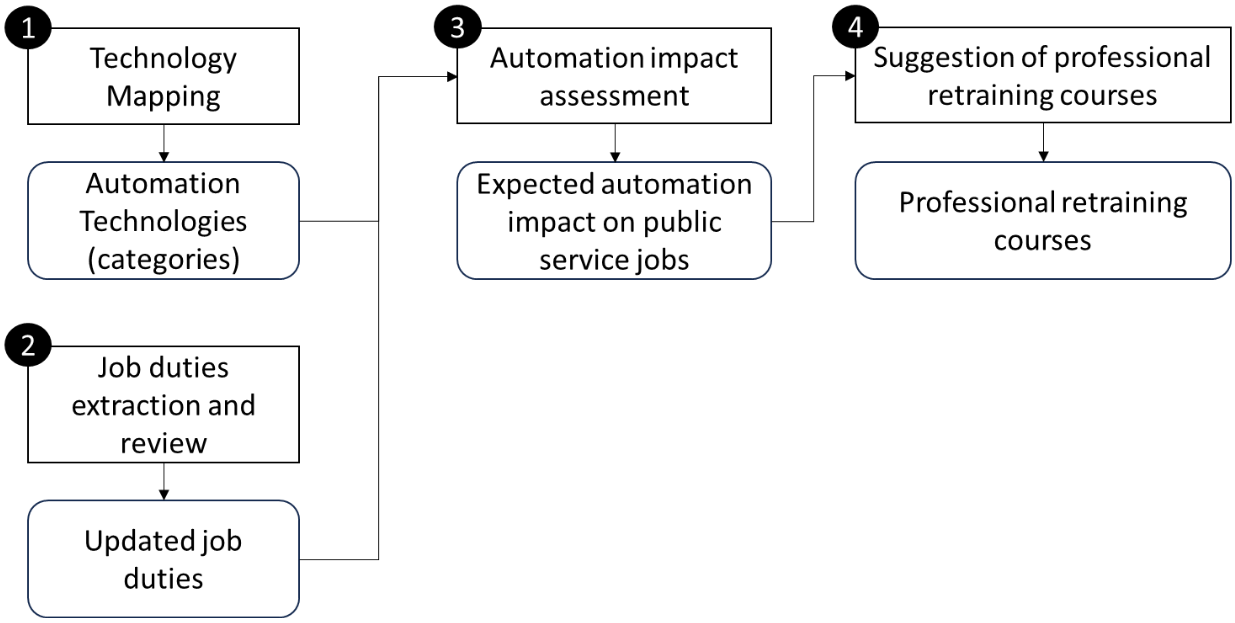

Figure 1: Summary of research methodology. Source: Created by the authors.

The assessment of the impact of automation on public jobs depends on two inputs: a list of automation technologies that are expected to impact the sector in the coming years and some type of job description that allows for a detailed analysis of the job. The first of these inputs is produced through a technology mapping based on the literature published in the last 2 years. The list of technology categories resulting from this process is then analyzed using ChatGPT 4 and Claude 2 to decide which are in fact categories of automation technologies and would have some impact on the job. Finally, ChatGPT 4 is used to provide a brief definition for each technology category and indicate 5 technologies that would be related to each one. The results of this first stage of the methodology are presented in Section 4.1.

To produce the second input required to assess the impact of automation, the job duties of the public positions to be analyzed were extracted and reviewed. As highlighted by previous research, there are a number of challenges in analyzing the positions and job duties of the Brazilian public sector given the lack of standardization in terms of code, name, and description, as indicated by previous studies (Adamczyk et al., 2021; De Oliveira Teixeira et al., 2022). In the case of the present research, an alignment of priorities was made with the Secretariat of Human Resources and the Secretariat of Labor Relations of the Ministry of Management and Innovation in Public Services (MGI) to decide which positions would be most relevant to be analyzed and which had some documentation that

[2] The prompts, codes and data produced during this research can be found at: https://drive.google.com/drive/folders/1kYqUzCRbaFB3YpfJij8KSOeiy-5thLr-?usp=sharing

gathered the job descriptions. With this, it was decided that the focus would be the analysis of intermediate-level (IL) positions and their job duties that are included in the Career Plan for Technical-Administrative Positions in Education (PCCTAE, in portuguese). The PCCTAE is a document published by the Federal Government, as part of Law No. 7.596 of 1987, that contains a list of 340 positions, of which 142 are intermediate level, and their responsibilities. It is important to note that some of these 142 positions exist in other agencies that are not in the education sector, which broadens the scope of the research.

The extraction and review of the job duties of the selected positions was done following the steps presented in Figure 2. The extraction was done using a Python code that processed the PCCTAE (pdf) file and generated a spreadsheet with the positions and their respective job duties. Then, another Python code sent the positions and job duties from the spreadsheet along with a prompt that asked the GPT-4 API to perform four activities. First, for each of the positions, GPT-4 should analyze the list of job duties provided and remove those that were considered obsolete, given that the list was written in 1987. Next, GPT-4 should expand or reduce the list of job duties for each position so that there would be a standardized number of 8 activities per position [3]. To record what GPT-4 did with the job duties for each position, it was asked to record whether each activity was: original, if the proposed job duty was the same as an activity in the original list; updated, if the proposed job duty was already on the original list, but something has been changed in the activity text; new, if the proposed job duty was created and was not on the original list. In the third activity, GPT-4 evaluated each job duty in terms of the frequency with which an average worker would perform each one, according to the scale below: rarely, once a year or less; occasionally, a few times a year, less than once a month; monthly, at least once a month, less than once a week; weekly, at least once a week, less than once a day; and daily, once or more times a day.

Finally, the last activity performed by GPT-4 was to define the degree of importance of each duty for the related position according to the scale: very low, low, medium, high and very high. The definition of frequency and degree of importance for each activity aimed to qualify the impact of automation, given that a high impact may be of little relevance for an activity that is rarely performed and of little importance for a given position. This type of classification is done by workers in catalogs of occupations and activities such as the one that exists in the USA (O*NET) and has not been used in previous studies, given the cost of producing something of this type for Brazil. However, GPT-4's ability to analyze data on occupations, proven in other previous studies, can be applied to enrich the analysis of the impact of automation by providing estimates for the frequency and degree of importance of the duties of the positions. The results of this step are presented in Section 4.2.

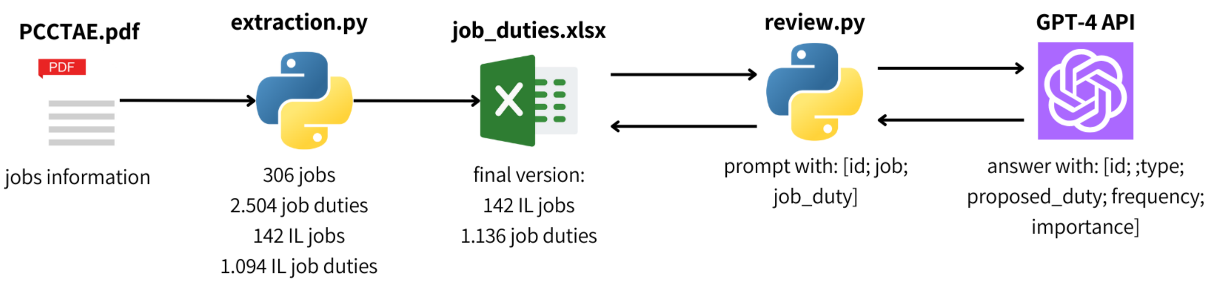

Figure 2: Details of the stage of extraction and review of public office duties. Source: Created by the authors.

Continuing with the research methodology, step 3 was the assessment of the impact of automation on the selected job roles (Figure 3). Here, a prompt (Appendix 2) for the GPT-4 Turbo API was developed with the categories of automation technologies, their descriptions, and related technologies resulting from step 1 of the methodology, and the job roles and duties resulting from step 2. In this prompt, GPT-4 Turbo was asked to respond with:

- A level of automation, according to the scale: Full (90-100%), High (70-80%), Medium (40-60%), Low (20-30%) and None (0-10%);
- Up to 3 categories of technologies and their respective technologies that would be used to automate attribution;
- An automation horizon, according to scale: immediate, available technologies could be adopted to perform the job duty; short term, in up to 2 years we would have technologies ready to replace the job duty;

[3] There is no ideal number of duties that a position should have, but the original PCCTAE list has a large variation in the number of duties, ranging from 2 to 29 duties. On average, there are 8 duties per position, and this number was adopted as being reasonable for standardizing the list.

medium term, it should take between 2 and 5 years for us to have technologies ready to replace the job duty; long term, it should take more than 5 years for us to have the technologies needed to replace the job duty.

To make it easier to understand the assessment made by GPT-4 Turbo, the prompt also asked for a justification for each of the above responses. In addition to helping to understand the logic behind GPT-4 Turbo's response, asking for a justification forces the model to "think" more carefully about its response. The results of this step are presented in Section 4.3.

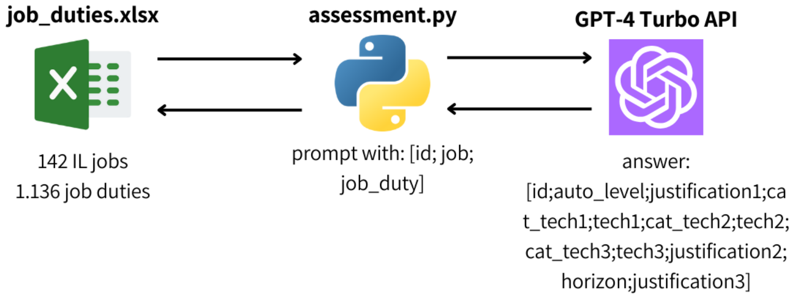

Figure 3: Details of the automation impact assessment stage. Source: Created by the authors.

The fourth and final stage of the research methodology involves suggesting courses for each position according to the duties and technologies related to each one. To do this, the GPT-4 Turbo API was once again called (Figure 4). This time, the prompt received as a response a list of courses, workload and syllabus for each position according to the duties and technologies related to each one. The results of this stage are presented in Section 4.4.

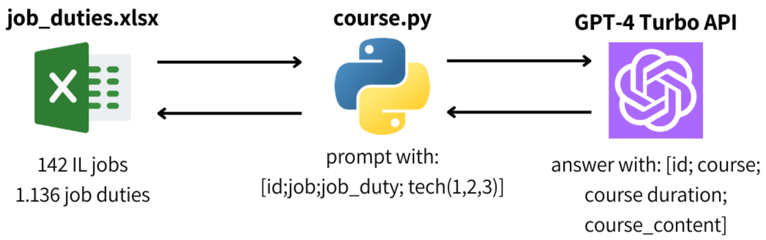

Figure 4: Details of the stage of suggesting professional retraining coursesThe use of footnotes should be avoided. Source: Created by the authors.

4. Results

This Section is structured to present the results of each of the stages of the methodology. Each of the stages generated products that are fully available in the research repository and are presented here to exemplify the results or analyze them quantitatively. Section 4.1 presents the results of the technological mapping, Section 4.2 presents the results of the extraction and review of the job duties of the positions analyzed, Section 4.3 presents the results of the technological assessment, and Section 4.4 presents the results of the suggestion of professional retraining courses.

4.1 Technological mapping

The literature review for the technology mapping was conducted based on technical papers published by organizations such as the World Economic Forum (WEF) and major consulting firms such as McKinsey, Deloitte and Gartner, which produce annual or biannual papers on technology trends. Given the differences in the names of technologies that exist from one paper to another, the list of technologies created from the mapping seeks to bring together, whenever possible, very similar technologies that have been named differently.

After listing all the technologies found in the papers, ChatGPT 4 and Claude 2 were asked to indicate which of them are automation technologies, given that some, such as Web 3, do not directly replace human labor, despite serving as a basis for the development of other technologies. Table 1 presents the result of this process.

The results were then reviewed by a human to ensure that no technology was left out and that the final list did not include technologies that did not belong to the automation technology category. As a result, encryption and cybersecurity technologies, synthetic data, and compression models that had been included by ChatGPT 4 were removed, but after stressing this with the model, the model itself recognized that it did not make sense to include them. In addition, digital applications and platforms and data analysis were included in the list due to their potential to replace duties and streamline processes. With the final list of automation technologies, some technologies were consolidated into technology categories so that they all had the same level of granularity.

In the last step of this process, ChatGPT was asked to write a brief description and list 5 automation technologies (avoiding overlap and repetition) related to each technology category that should be considered in a study on the impact of automation on work. This led to the final list of automation technology categories which included: Data Analytics, Digital Applications and Platforms, Applied AI, 3D Printing, Internet of Things, Robots, and Extended Reality.

Table 1: Mapped technologies and evaluation results of ChatGPT 4 and Claude 2. Source: Created by the authors.

	Source						**Automation technologies**	
Technology	**WEF**	**McKinsey**	**Deloitte**	**Accenture**	**Gartner**	**FTI**	**ChatGPT 4**	**Claude 2**
Digital platforms and apps	x							
Education and workforce development technologies	x							
Big-data analytics	x		x	x			x	x
IoT and connected devices	x			x			x	x
Cloud computing (and Edge computing)	x	x	x		x		x	x
Encryption and cybersecurity / Trust architectures and digital ID	x	x	x	x	x		?	
E-commerce and digital trade	x							
Artificial Intelligence	x		x	x	x	x	x	x
Applied AI		x		x	x		x	x
Industrializing ML		x					x	x
Generative AI		x		x	x	x	x	
Self-supervised learning					x		x	
Environmental management technologies	x							
Climate-change mitigation technology	x	x				x		
Text, image and voice processing	x						x	x
Augmented and virtual reality / Immersive reality technologies / Extended reality / Metaverse	x	x	x	x		x	x	
Power storage and generation	x							
Electric and autonomous vehicles	x	x				x	x	x
Robots / and drones	x					x	x	x

Next-gen software development		x	x	x				
Web3		x	x	x		x		
Advanced connectivity		x						
Quantum technologies		x	x	x		x		
Biotechnology / Bioengineering		x				x		
Space technology		x						
Electrification and renewables		x				x		
Synthetic data					x		?	
Model compression					x		?	
3D and 4D printing and modeling	x						x	x
Nanotechnology	x							

4.2 Extraction and review of job duties

The process of extracting PCCTAE job duties resulted in a list with 142 intermediate-level positions and their 1,093 related job duties that were reviewed by GPT-4 to analyze obsolescence, given that the original document is from 1987, and to include information regarding the frequency of execution of the job duties and their importance. Table 2 shows the response given by GPT-4 for the driver position. In this case, GPT-4 kept 3 of the original job duties, updated one of them, only changing the text to simplify it, and included four new job duties to reach a total of 8, as requested in the prompt. The frequencies and degree of importance of each of the job duties were included so that it is possible to differentiate those that would have the greatest impact on the position in the event of automation.

Table 2: Example of a review of duties for the position of driver. Source: Created by the authors.

Job duty	**Type**	**Frequency**	**Degree of importance**
Use navigation system and route planning	New	Daily	Very important
Test the brakes and electrical system	Original	Monthly	Extremely important
Drive the vehicle	Original	Daily	Extremely important
Arrange for vehicle maintenance	Updated	Occasionally	Very important
Perform emergency repairs to the vehicle	Original	Rarely	Moderately important
Record mileage and fuel consumption	New	Weekly	Moderately important
Check and maintain safety equipment	New	Monthly	Extremely important
Perform daily inspections and safety checks on the vehicle	New	Daily	Very important

Figure 5 shows the distributions of type, frequency and degree of importance resulting from the review process, which resulted in 1,136 job duties. It is possible to see that GPT-4 kept just over 33% of the original job duties, either as they were already written (22%) or updated (11%), with the rest being new. Regarding the frequency distribution, 96% were considered to be performed weekly (45%) or monthly (41%), with only 0.1% of the job duties being rarely performed. Finally, the degree of importance most associated with the job duties was very important, with 52%, followed by moderate, with 30%, and extremely, with 17%. As GPT-4 reviewed the list of job duties and asked to prioritize those that were truly important, none of them received a degree of no importance and only 0.3% were considered somewhat important (low).

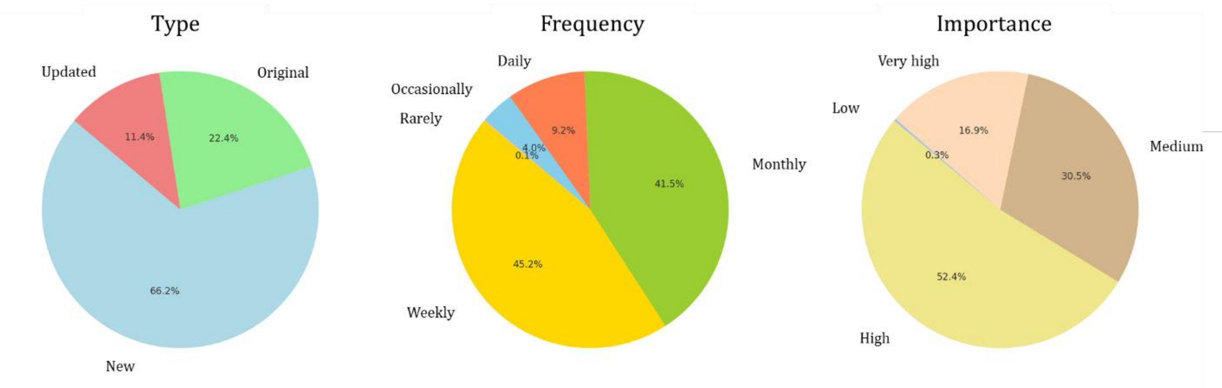

Figure 5: Type, frequency and importance distributions of revised job duties. Source: Created by the authors.

4.3 Assessment of the impact of automation

The automation impact assessment process, carried out with GPT-4 Turbo, resulted in a large amount of information regarding the level of automation, the technology and technology categories and the automation horizon for each of the 1,136 job duties, in addition to the justification for the responses given.

The example below show how the automation impact assessment was done for one job duty.

Position: Props

Job duty: Assemble, transform or duplicate scenographic or costume objects

- Automation level: Medium (40-60%)
    - Rationale: Automation can help with the assembly and duplication of objects
- Technology categories: 3D Printing and Extended Reality
- Technologies: Metal 3D Printer and Augmented Reality (AR)
    - Rationale: 3D printing for three-dimensional objects. AR for visualization and precise adjustments during creation
- Horizon: Short term (< 2 years)
    - Rationale: Advanced 3D printing and AR technologies are still under development for use in stage design

The evaluation exemplified above was made for the 1,136 job duties, with the most frequent level of automation being medium with 507 (44%) job duties, followed by high (295 or 26%) and low (291 or 25%) who had practically the same number of job duties (Figure 6). Less than 4% of the job duties were in the "none" (37) and "total" (6) levels.

Regarding the automation horizon, 817 (72%) job duties were between immediate (411) and short-term (406), 250 had a medium-term horizon and 69 had a long-term horizon (Figure 7).

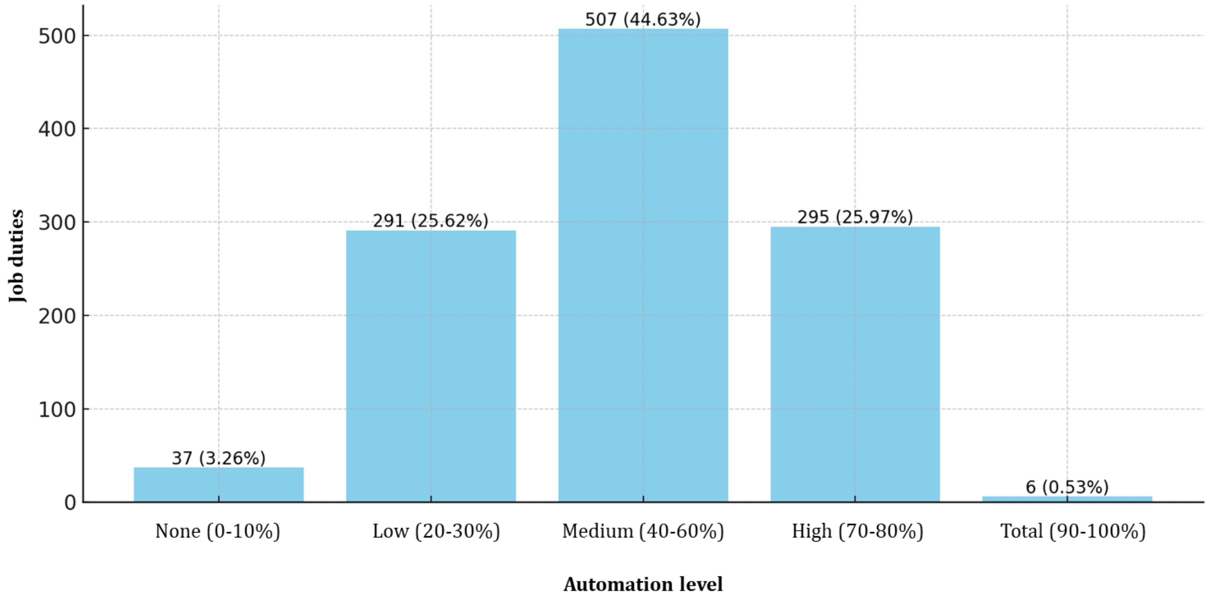

Figure 6: Job duties' automation level. Source: Created by the authors.

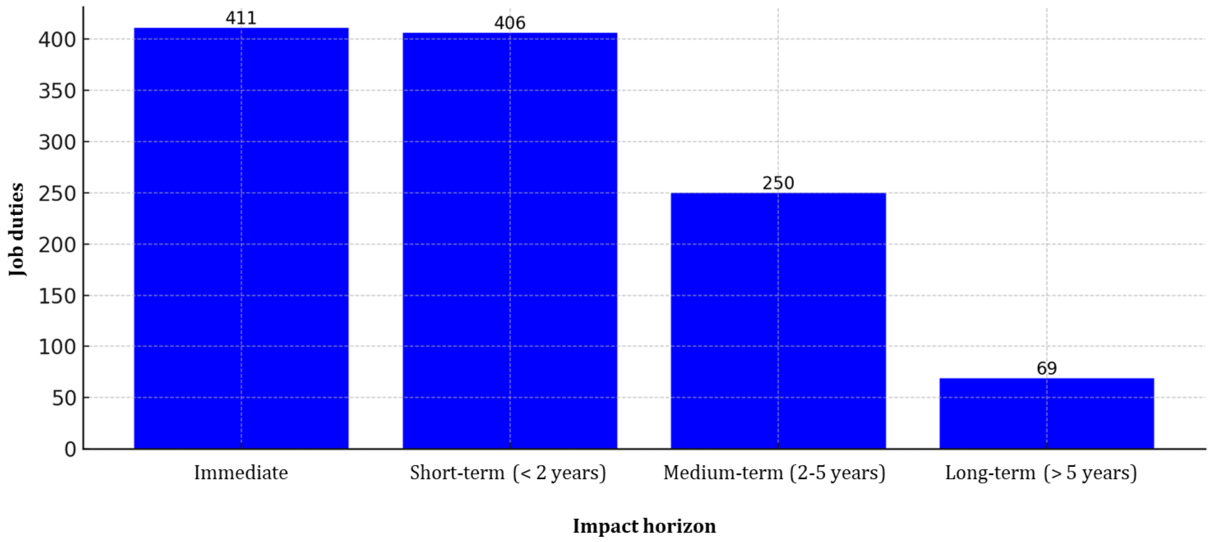

Figure 7: Technologies' impact horizon. Source: Created by the authors.

The calculation of normalized impact (In) for each position was made using the following formula:

$$In = \frac{\frac{\sum f \ x \ imp \ x \ lev_{auto} \ x \ hor}{400}}{8}$$

Being:

f the frequency of job duty

imp the degree of importance of the job duty

lev_{auto} the level of automation of the job duty

hor the horizon of attribution automation

It is important to highlight that the variable frequency of the job duty can assume the following categories and associated values: rarely (1), occasionally (2), monthly (3), weekly (4), and daily (5). Meanwhile, the variable importance of the job duty can assume these values: very low (1), low (2), medium (3), high (4) and very high (5). Automation level, in its turn, ranges from none (0) to total (4). Finally, horizon is scored from immediate (4) to long-term (1). As such, the product of these variables can reach a maximum value of 400, which justifies the division by 400 to normalize the result. Finally, the normalized sum is divided by 8, corresponding to the number of job duties evaluated per position, resulting in the average impact score for that position.

From this calculation, we have the percentage distribution presented in Figure 8, which divides the values In found in the assessment into 10 groups. We can see that the maximum impact we have is in the range of 0.47 to 0.52, with less than 1% of the positions, on a scale that can reach up to 1, if frequency, importance, level of automation and horizon are all at the maximum levels. The largest number of positions is in the range of 0.24-0.28, followed by the previous ranges, 0.19-0.24 and 0.15-0.19. Figure 9 and Figure 10 show the 10 positions with the highest and lowest values In found in the assessment.

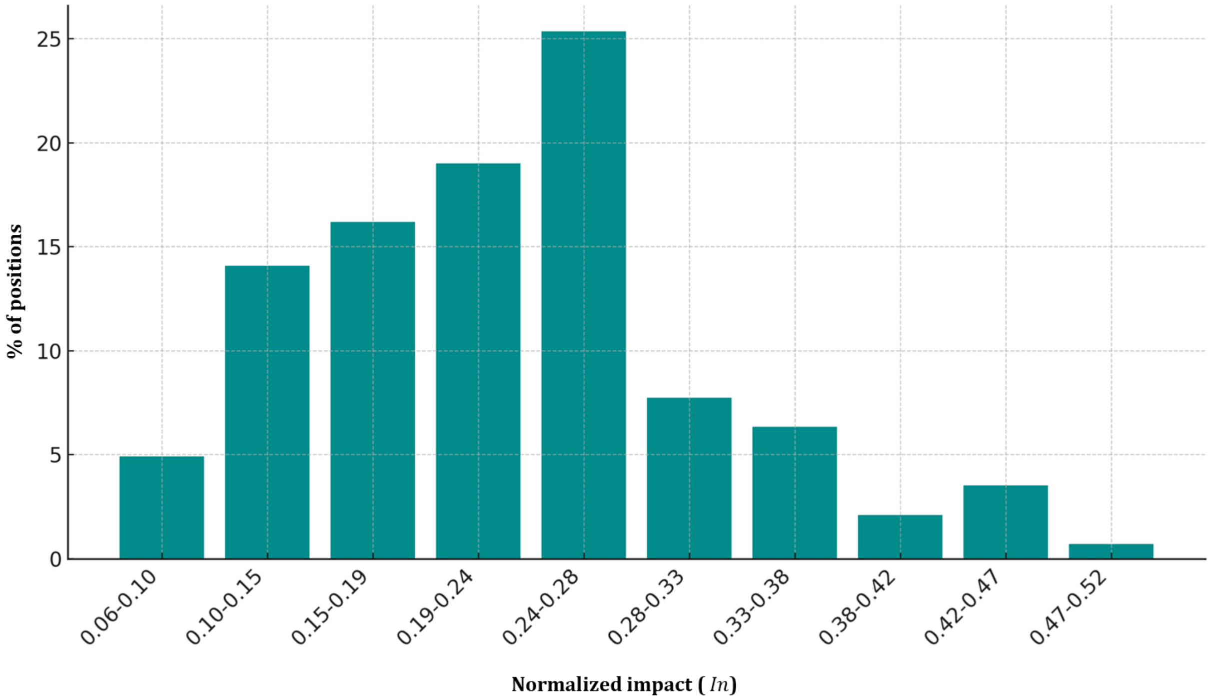

Figure 8: Percentage distribution of positions by impact range of the normalized impact. Source: Created by the authors.

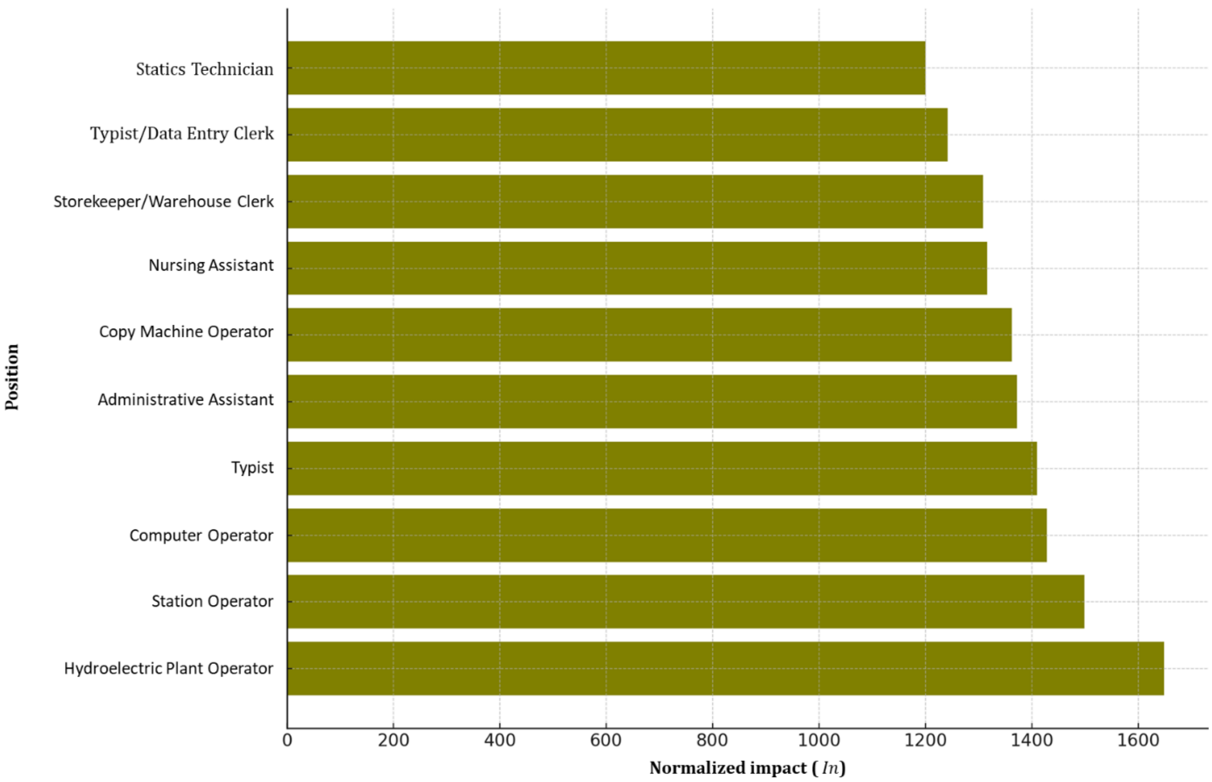

Figure 9: Top 10 positions with the highest normalized impact. Source: Created by the authors.

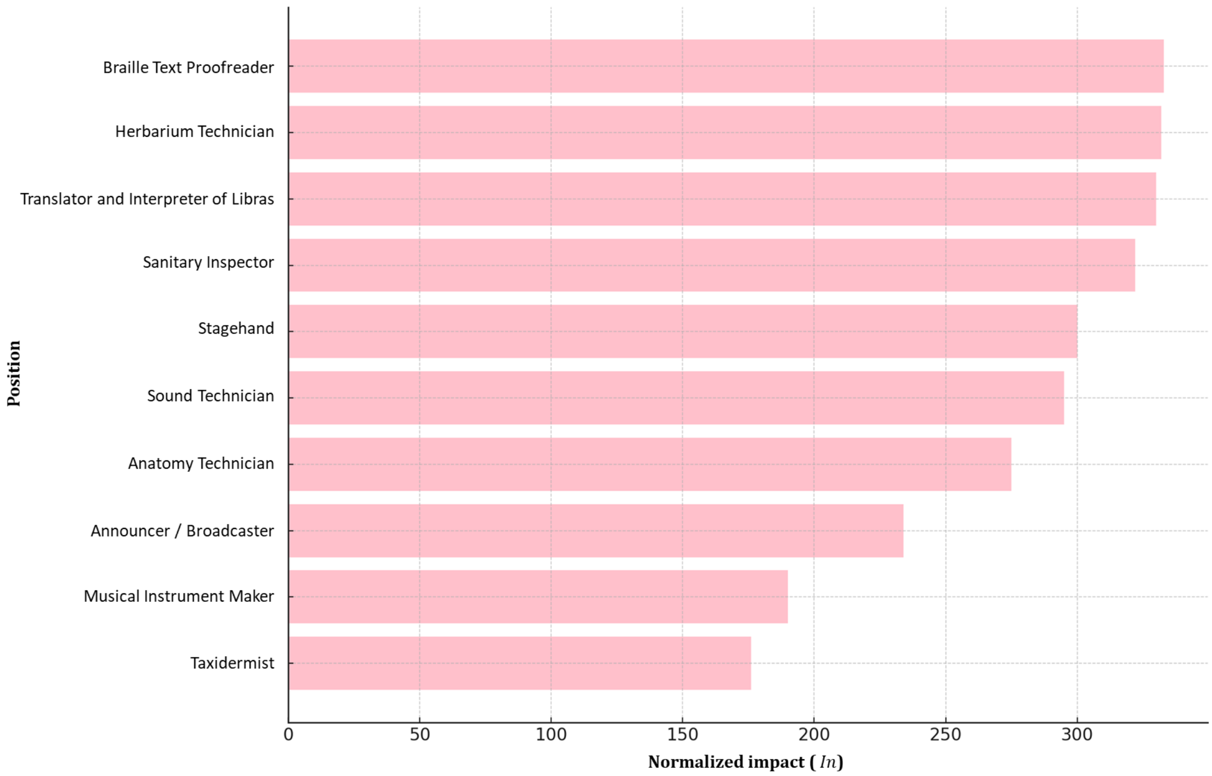

Figure 10: Top 10 positions with the lowest normalized impact. Source: Created by the authors.

Finally, the technology categories that appeared most frequently in the assessment of the impact of automation were Applied Artificial Intelligence (AAI) with 600 occurrences, Digital Applications and Platforms (APP) with 452 occurrences, and Data Analytics (DA) with 382 occurrences (Figure 11). The least cited category was 3D Printing (PRT), with only 25 occurrences. In total, GPT-4 Turbo associated 59 technologies with the 1,136 job duties evaluated (Table 3). Considering that 35 technology examples were given, 5 per category, GPT-4 Turbo needed to suggest 24 more technologies to evaluate all job duties. The list below shows the 10 most cited technologies:

1. Machine Learning: 323 occurrences
2. Smart Sensors: 169 occurrences
3. Process Digitization Systems: 163 occurrences
4. Online Communication and Collaboration Platforms: 104 occurrences
5. Business Intelligence (BI): 100 occurrences
6. Natural Language Processing (NLP): 100 occurrences
7. Data Mining: 93 occurrences
8. Big Data Analytics: 82 occurrences
9. Task and Project Management Systems: 77 occurrences
10. Robotic Process Automation (RPA): 64 occurrences

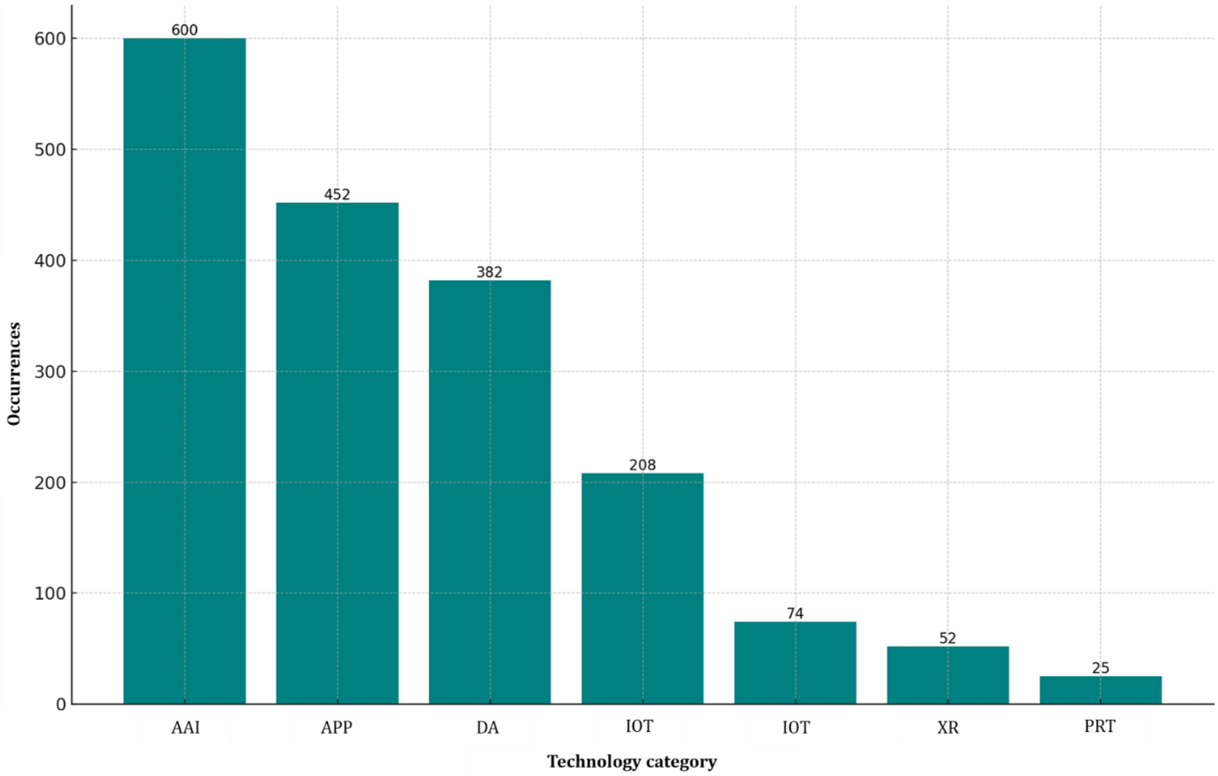

Figure 11: Frequency of technology categories with labels. Source: Created by the authors.

Table 3: List of technology categories (cat_tech) and technologies (tech) listed. Source: Created by the authors.

cat_tec	tech	cat_tec	tech
DA	Big Data Analytics	AAI	Machine Learning
DA	Business Intelligence (BI)	AAI	Natural Language Processing (NLP)
DA	Data Mining	AAI	Recommendation Systems
DA	Data Visualization	AAI	Test Automation Software
DA	Predictive Analytics	AAI	Computer Vision
DA	Data Visualization	PRT	Bioprinting
APP	CAD/CAM Software	PRT	3D Printing in Construction
APP	Online Forms	PRT	Metal 3D Printers
APP	GIS	PRT	FDM 3D Printers
APP	Laboratory Information Management Systems (LIMS)	PRT	Multi-material 3D Printers
APP	Online Communication and Collaboration Platforms	IoT	IoT Gateways
APP	E-learning Platforms	IoT	IoT Management Platforms
APP	Digital Rights Management Platforms	IoT	IoT Communication Networks
APP	Streaming Platforms	IoT	Smart Sensors
APP	Cryptography and Security Systems	IoT	Automated Control Systems
APP	Process Digitization Systems	IoT	Wearable Technology
APP	Video Editing Systems	RBO	Drones
APP	Digital Content Management Systems	RBO	Robotic Exoskeletons
APP	Document Management Systems	RBO	Autonomous Robots
APP	Event Management Systems	RBO	Collaborative Robots
APP	Information Management Systems	RBO	Cleaning Robots
APP	Sustainability Management Systems	RBO	Service Robots
APP	Task and Project Management Systems	RBO	Industrial Robots

APP	Measurement and Inspection Systems	RBO	Autonomous Vehicles
APP	Navigation Systems (GPS)	XR	Augmented Reality (AR)
APP	Information Security Systems	XR	Mixed Reality (MR)
APP	Decision Support Systems	XR	Virtual Reality (VR)
APP	Office Productivity Suites	XR	Interactive Simulations
AAI	Robotic Process Automation (RPA)	XR	VR/AR
AAI	Generative AI		

4.4 Suggestion of retraining courses

The last step of the methodology was the suggestion of retraining courses, which resulted in 236 courses for the 141 positions analyzed. Each course is accompanied by a list of topics and a suggested workload. The example presented in Table 4 for the Props position illustrates the results of this course suggestion process that was carried out with GPT-4 Turbo.

Table 4: Example of suggested courses for the position of Props Specialist. Source: Created by the authors.

Course	**Topics**	**Duration (in hours)**
3D Metal Printing Props Design and Manufacturing Course	Prop Design Fundamentals, Metal 3D Printing Materials and Techniques, Metal Post-Processing Processes for Props.	120
Instrument Conservation Course with Smart Technologies	Smart Sensors applied to Conservation, Preventive Maintenance Planning, Monitoring Methods and Conservation of Props.	60
Process Digitization Course for Prop Specialists	Introduction to Process Digitization Systems, Tools and Practical Applications, Cloud Data Management and Storage for Props Projects.	80
Course in Augmented Reality and Artificial Intelligence for Prop Design	Principles of Augmented Reality and Generative AI, Application in Artistic Design and Prop Production, Integration of AR in Artistic Production Environments.	100
Course on Communication and Collaboration in Artistic Productions with NLP	NLP Fundamentals for Team Articulation, AI-Assisted Communication Tools, Communication Strategies and Collaboration in Artistic Projects.	40
Advanced Course in Big Data Analytics for Sustainability in Props	Introduction to Big Data for Sustainable Materials Research, Data Analysis and Visualization, Sustainable Materials Implementation Strategies.	90
Computer Vision Course applied to Prop Quality	Fundamentals of Computer Vision, Automated QA Systems, Integration with Real-Time Production.	70

5. Conclusion

Assessing the impact of automation is not new in academia, including scenarios outlined for Brazil. However, few studies have addressed the specific case of automation in the public sector. The challenges in dealing with this issue in public management are even greater than those faced by the private sector and include barriers to creating or eliminating positions. In this sense, it is essential not only to frequently assess the impact of automation on public positions, given the rapid technological advances and the benefits this brings to the services provided to the population, but also to observe possibilities for professional retraining for public servants.

In this sense, the present study seeks to meet these two demands through the use of a modern methodology for assessing the impact of automation that uses Generative AI technologies such as Claude 2 and GPT-4 Turbo to evaluate a large and diverse number of positions quickly and that allows easy reproduction for other cases.

In addition to the methodology itself, the study provides some intermediate results that are contributions in themselves. The technological mapping of recent literature on emerging technologies allowed us to map, define and exemplify 7 categories of automation technologies that are important for the public sector to monitor, given their potential for implementation in a wide range of areas. The extraction and review of the job duties allowed us to create a new list of job duties for public positions that were defined in 1987. In addition, the frequency and degree of importance of the 1,136 job duties resulting from this process gave a degree of detail to the study and enriched the definitions of the positions analyzed.

The main results of the study involved assessing the impact of automation and suggesting professional retraining courses. The assessment produced a wide range of information that allows us to understand both the level of automation of each job duty and position and a breakdown of this impact with each related technology, an automation horizon and justifications for each of these elements. The level of automation of the job duties was concentrated in the low, medium and high impact range, while the horizon is much more immediate and short term, demonstrating great potential for automation of the intermediate level positions that were analyzed. Despite this potential, when compared with the frequency, the degree of importance and the automation horizon itself, it was possible to see that the positions are concentrated in a range of 0.10-0.28 points out of a maximum of 1 and that no position exceeds 0.52 points. In terms of technologies, the ones that stood out the most were Machine Learning, Intelligent Sensors and Process Digitization Systems, with the most cited technology category being Applied Artificial Intelligence.

The suggestion of professional retraining courses was a new process for the literature in the area, but essential for dealing with automation in the public sector given the limitations of personnel management that exist in this area. 236 courses were generated with their respective syllabuses and workload.

The limitations of this study include those inherent to the technologies used, such as the hallucinations that Claude 2 and ChatGPT/GPT-4 sometimes demonstrate, and the data limitations of the training databases. The GPT-4 Turbo model represents an evolution in the face of these limitations and produced satisfactory results throughout the study, which were manually reviewed to ensure the quality of the final products. The tendency is for these models to evolve in the future and continue to surprise us with their potential for application in studies related to the impact of automation. Furthermore, the study is based on a list of duties that was developed in 1987 and updated for 2023. This process may mask a possibly greater impact of automation given that it is not known exactly what the real duties of public servants who occupy the positions analyzed are in 2023. Thus, this study, as well as any other that deals with a large number of positions or occupations, requires analyses at the individual level of the occupation or of a set of similar occupations that allow us to understand the organization of work in order to bring the analysis closer to the reality of public positions.

Future studies can expand the analysis presented here to other positions in the public sector, as well as develop methodologies that allow for a more in-depth process of suggesting retraining courses to support the creation of complete courses with a description of empirical and theoretical approaches at the forefront of science and a suggestion for the application of contextualized active methodologies. In addition, the technologies applied in this research can be used to help public servants better explore how to use automation technologies as allies in the process of delivering public services with better quality and efficiency.

Finally, as a future research agenda, the aim is to assess the impact of automation considering the criteria of gender, race, and their intersectionality. In a racist and sexist country like Brazil, where the composition of the public sector is still not representative of the population, it is essential to analyze automation through these social markers and critically examine its differentiated effects.

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