Automation in public sector jobs and services: a framework to analyze public digital transformation's impact in a data-constrained environment

Received 11 April 2023
Revised 2 August 2023
7 September 2023
Accepted 25 September 2023

Andrea Bonomi Savignon, Riccardo Zecchinelli, Lorenzo Costumato and Fabiana Scalabrini
Department of Management and Law, University of Rome Tor Vergata, Roma, Italy

Abstract

Purpose – This study aims to estimate the value of the impact from digital transformation (DX) focusing on its automation effect, looking at the time and cost savings coming from the substitution effect with an adoption of digital technologies. For example, cloud and artificial intelligence technologies such as ChatGPT have the potential to change ways of working, substituting and replacing several of the tasks that are currently carried out by public administration (PA) employees and labor processes underpinning PA services.

Design/methodology/approach – The paper outlines a new framework to estimate the potential impact of DX on the public sector. The authors apply this framework to estimate the value of the impact of DX on the Italian PA, defining the latter by the collection of the value of its labor (i.e. PA workforce salaries) and by the collection of the value of its outputs (i.e. public services' costs).

Findings – This study ultimately maps out the magnitude and trends of how likely the PA occupations and services could be substituted in a wider process of DX. To do this, the authors apply their framework to the Italian PA, and they triangulate secondary data collection, from official accounts of the Italian Ministry of Economics and the National Statistical Institute, with methodological antecedents from the UK Office for National Statistics and experts' insights. Results provide a snapshot on the type and magnitude of PA jobs and services projected to be affected by automation over the next 10 years.

Originality/value – To the best of the authors' knowledge, this paper provides for the first time an approach to estimate the value of the impact of DX on the public sector in a data-constrained environment – or in the lack of the required primary data. Once applied to the Italian PA, this approach provides a granular map of the automatability of each of the PA occupations and of the PA services. Finally, this paper mentions preliminary insights on potential challenges related to equity in public sector jobs and implications on recruitment processes.

Keywords Digital transformation, Public sector jobs, Automation, Public services

Paper type Research paper

Transforming Government: People, Process and Policy
Emerald Publishing Limited
1750-6166
DOI 10.1108/TG-04-2023-0044

1. Introduction and background

The issue of efficiency, effectiveness and productivity is not a new topic in public digital transformation (DX) research. The adoption of DX carries great promises to improve government efficiency in terms of lower costs or increased revenues and effectiveness, to improve citizen service delivery, to create new types of services that were not previously available, to increase the accessibility of those services and to transform government itself through automation. The search for efficiency has been one of the most important drivers of ICT use in government, and most national strategies specifically address this goal. The pursuit of efficiency sees as its objective not only the reduction of overall spending but also the allocation of funds to higher priority areas (Lee and Perry, 2002; Brown, 2001; Moon and Norris, 2005; OECD, 2003; Luna-Reyes *et al.*, 2012).

However, although many DX programs have been started under this effigy, and measurement becomes fundamental in a model of continuous improvement, today little is still known about the impact in terms of efficiency of DX initiatives, partially because of a lack of effective measures to evaluate these aspects (Carbo and Williams, 2004; Kunstelj and Vintar, 2004; Esteves and Joseph, 2008). Intelligent automation and artificial intelligence (AI) technologies such as ChatGPT are an example of DX adoption that policymakers are addressing across the public administration (PA), despite a significant lack of evidence about their expected impact on resources and processes (Campion *et al.*, 2022; Kuziemski and Misuraca, 2020).

There is a multitude of definitions for DX: it encompasses both process digitization with a focus on efficiency, and digital innovation with a focus on enhancing existing physical products with digital capabilities (Berghaus and Back, 2016) as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" (Vial, 2019).

Significantly, technological advances are leading to the development of a spectrum of digital workforce tools that organizations can use to automate their processes. At one end of the digital workforce spectrum is basic automation, which uses technology to manipulate existing software to complete a process. At the other end of the spectrum is AI, which is software able to learn by analyzing data and then refining future performance (Cooper *et al.*, 2019).

According to Kaplan and Haenlein (2020), AI can be understood as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation."

Despite their undeniable relevance, the analysis of impacts that DX-enabled automation brings on the workforce, organizational structures, economy, government or society remains largely incomplete (de Sousa *et al.*, 2019; Alon-Barkat and Busuioc, 2023).

More specifically, in the public sector, automation through DX can support the decision-making processes of public employees through the application of pre-established rules to existing data (Kuziemski and Misuraca, 2020). However, DX and the consequent automation cannot entirely replace civil servants' work, as the reality of the individual citizen who requests a service has specificities from time to time, that will never fully correspond to the general law or regulation. Therefore, human judgment remains essential to delivering public services (Borry and Getha-Taylor, 2019; de Boer and Raaphorst, 2023). The above should not lead to believe that DX does not bring with it enormous opportunities for change, along with associated risks, for the public sector.

The focus of our work is on measures such as efficacy, efficiency, productivity and savings that DX generates. On one hand, services are expected to be more effective and efficient, and on the other hand, the application of DX opens up problems such as the right to equal access, fair treatment and privacy for citizens, and on the organizational side, it brings back the known issues of DX and unemployment risks, and the question of accepting far-reaching changes in organizational structures and culture for employees and users to accept innovation (Willems *et al.*, 2022; Neumann *et al.*, 2022; Andersson *et al.*, 2022).

The radical effects of DX on employment could take fundamentally two forms: a negative and substitution effect on labor demand due to technological replacement of human activities and skills, and a positive and complementary effect due to the creation of new industries and jobs (Frey and Osborne, 2017).

Based on these premises, the aim of this paper is to offer a new methodology to map out the immediate automation effects from DX on the public sector. In the existing literature, we observe a significant gap on how public management could measure the value of DX impact (i.e. immediate effects based on DX automation effects, interpretable as opportunities and downsides) based on an evidence-based approach, especially in a data-constrained environment.

A growing interest to have a human centric and inclusive DX adoption is observable both in theory and practice, yet current literature does not highlight how the distributional impact might be mapped across the PA. This methodology might be useful for policymakers to map out where most support is needed in terms of digital skills and competencies, and to better prioritize investment decisions and appraise potential opportunities and risks.

The paper is organized as follows. Section 2 analyzes the existing literature on the effects of DX-enabled automation in the public sector, and the main antecedents on automatability estimation. Section 3 illustrates the data and the different methodologies used in our analysis, distinguishing between estimates based on professions and on public services. Section 4 illustrates the findings. Section 5 provides a discussion of the findings and policy implications, whereas Section 6 concludes, also suggesting avenues for further research on the topic.

2. Literature antecedents on automatability or probability of automation from public digital transformation processes

In the literature, it is possible to distinguish between two main effects from a widespread DX adoption in organizations (Brynjolfsson and McAfee, 2014; Daugherty and Wilson, 2018; Davenport and Kirby, 2016): automation, that implies machines taking over human tasks, and augmentation, in which humans interact with machines to perform tasks. An intrinsic tension among these two effects of DX must be addressed, as DX automation effect would substitute human activities and skills for process rationalization and efficiency reasons (Davenport and Kirby, 2016), whereas DX's augmentation effect would enhance employees' effectiveness and productivity.

Despite a broad consensus on this tradeoff, these two effects cannot be neatly separated from a managerial perspective. Organizations adopting digital technologies have to be aware of these tradeoffs between complementarity and substitution, and between automation and augmentation effects. Following this theoretical approach, Raisch and Krakowski (2021) have argued that automation and augmentation effects from DX technologies are simultaneously contradictory but interdependent.

In 2017, Frey and Osborne (2017) implemented a novel methodology estimating the probability of computerization on jobs in the labor market, based on an algorithm able to identify the automatization or computerization of a specific job within the next 10–20 years, on the grounds of whether the overall job could be automated thanks to a widespread DX.

The authors could find, using their algorithm, the probability of automation based on a series of computerization bottlenecks, across all occupation categories in the US labor market.

Digitalization or computerization bottlenecks are indeed those job's attributes that would be unlikely to be computerizable or automatable by emerging digitalization in the near future. In a nutshell, these bottlenecks include those variables that require the following:

- *High level of perception and manipulation* – For example, when sophisticated non-repetitive, manual dexterity is required or those jobs where cognitive skills are needed with non-machine-readable data, e.g. in terms of problem solving.
- *Creative intelligence* – For example, when a specific job requires a high level of original, unusual ideas about a given topic or situation, e.g. in fine arts.
- *Social intelligence* – All those jobs that require a high level of social perceptiveness, negotiation, persuasion and assisting and caring for others, e.g. nurses and doctors.

Applying such analysis on the US labor market, they looked at the *substitution effect* of future computation on the mix of jobs across sectors distinguishing between high, medium and low risk occupations, based on their probability of computerization (thresholding at probabilities of 0.7 and 0.3).

The Frey and Osborne (2017) approach for probability of automation assumed that whole occupations rather than single job-tasks are automated by technology. This might have led to an overestimation on probability of automation, and hence risk of displacement.

For this reason, we looked at the OECD study by Arntz *et al.* (2016) that considered the heterogeneity of workers' tasks within occupations. As said, as occupations usually consist of performing a bundle of tasks, not all of which may be easily automatable, the potential for automating entire occupations and workplaces may be much lower than suggested by the approach followed by Frey and Osborne.

Based on such adjustments, the OECD paper was then able to estimate what jobs would be most/medium/least at risk of automation (using the same thresholding at probabilities of 0.7 and 0.3), based on their probability of automation applied to jobs for 21 OECD countries using a task-based approach.

Arntz *et al.* predict that more jobs are likely to experience change than be automated. In the UK, this is 25% and 10%, respectively. Change is likely when 50%–70% of tasks are automatable, whereas automation is likely when more than 70% of tasks are automatable.

Relying on such approach, recently the UK Office for National Statistics (ONS, 2019) produced estimates on occupations at risk of automation based on their underpinned probability of automation, based on the nature of their tasks and in a context of increasing DX.

The ONS analysis looked at the tasks performed by people in jobs across the whole UK labor market, to assess the probability that some of these tasks could be replaced through automation.

They identified that probability of automation tends to be higher for lower-skilled roles involved in routine and repetitive tasks, that can be carried out more quickly and efficiently by an algorithm written by a human, or a machine designed for one specific function. The three occupations with the highest probability of automation were estimated to waiters and waitresses, shelf fillers and elementary sales occupations, all of which are low skilled or routine.

The automation estimates do not have a time element attached to them, but they can be interpreted as “the probability that this occupation will be partially, or fully, automated in the future.” The ONS approach used the OECD task-based approach to obtain these estimates; the probabilities of automation can be not strictly interpreted as the percentage of tasks to be automated, rather than an overall probability of automation, calculated by looking at what impact each task within an occupation has on this figure.

Few studies have sought to apply these estimates to a specific national context. Using a measure of automation susceptibility, Adamczyk *et al.* (2021) show that approximately 20% of Brazilian Public Sector employees work in jobs with a high potential of automation in the coming decades.

Still, so far, none of these antecedents have attempted to apply these estimations to a measure of value of PA employment or PA services, to assess the magnitude of effects by DX-enabled automation. A point of novelty of our study is that we suggest using these automatability estimates with a precise purpose: to measure the actual economic value of the automation impact of DX, based on the aggregated displacement effect on the PA workforce or services.

3. Data and methods

In this section, we outline the main research methods and data used in this paper to appraise the scale and distribution of impacts from DX in the public sector, with a specific focus on its immediate automation effects.

Despite an accelerated uptake of emerging technologies and an increased interest from governments for DX across the whole public sector, most policymakers and public managers are not actually able to target public policies and investments, given they lack evidence to appraise which are the high-impact areas (OECD, 2020). Given the lack of “bottom up” primary data on what are the direct and indirect benefits, costs and risks from the adoption of digital technologies across the PA, governments might tend to draw their interventions based on anecdotal evidence from the private sector or based on off-the-shelf strategic priorities.

While there is not a sound and agreed approach on measuring the impact of DX in terms of augmentation and productivity effects, in recent years a consolidated body of work across the economics and management literatures has been formed to measure the automation effect of DX on organizations’ business models and workforce.

Indeed, our paper proposes a new framework for public managers to map out the value of the impact from a widespread DX on the PA, focusing only on the automation effects (automatability), disregarding for now the augmentation and productivity effects.

3.1 A new approach to seize the value of the impact from digital transformation on public administration

Focusing only on the automation effect, public managers might be able to estimate the impact of DX by applying the estimates on the probability of automation for PA occupations or PA services to the PA value, proxied by the cost of PA services or by the cost of PA workforce.

Given most OECD countries have developed a PA annual accounts data set on workforce and services, its public managers might be able to overcome the challenges from lack of primary data on the impact of digital technologies uptake using instead this new suggested methodology.

First, our approach would require policymakers and public managers to estimate the *value of a country’s PA or public sector*; this can be based on its internal and external impact.

Overall, we can identify two different approaches: an *accounting-based input-output* approach (where its outputs equal the costs of inputs and intermediate-inputs) and a *quality-adjusted approach* (where experimental analysis attempts measuring PA's outcomes adjusting the value of outputs). For simplicity and the purpose of this paper, we suggest public managers could use the cost of PA's inputs to proxy the value of a PA.

Given the commonality across countries' accounting systems, we suggest the following measures for public sector's inputs:

- the cost of PA workforce; and
- the cost of PA services.

Second, to implement such an approach, public managers would need to identify the *probability of automation* for PA workforce or for PA services.

As mentioned in the previous section, significant work has been done to estimate the probability of displacement or automation of jobs based on the mix and nature of its tasks, but we propose that a similar framework can be used also to estimate the impact on PA services.

The automatability estimates can be gathered based on secondary data, such as publicly available external estimates, or primary data, such as estimates obtained directly by experts with a theory-based structured survey consistent with the approach of previously mentioned studies.

Main studies such as Arntz *et al.* (2016) and ONS (2019) consider highly automatable public services or jobs when automation probability is or higher than 70%, based on the underpinning tasks/processes.

Similarly, they consider medium automatability with a probability of automation between 30% and 70%, based on underpinning tasks. Low automatability is defined when the automation probability is less than 30%, having considered its tasks.

These estimates are based on an average of scale-based scores where each expert consulted in those studies was requested to appraise the automatability of a job or a service based on the three already mentioned main cluster criteria:

(1) extent of level of perception and manipulation;
(2) creative intelligence; and
(3) social intelligence requested to deliver the mix of tasks or processes underpinning a PA job or a service.

Immediate automation effect of DX from substituting jobs' tasks and services can be interpreted in a twofold manner: the uptake of digital technologies promises to lead to significant savings in terms of time and resources, but at the same time such displacement effect might need to be interpreted as a risk of job displacement, that could lead to increased income inequality. This latest aspect will be further expanded in the discussion section.

To condense what said so far, our new framework in seizing the automation effects from DX on a PA can be outlined as below:

$$Value\ of\ the\ DX\ on\ a\ PA = \left\{\sum PA\ value\right\} x\ \{\%\ PA's\ service\ or\ \%PA's\ job\}$$

The total value of the impact of DX on a PA or public sector would be the result of a two-stage process.

First, public managers would need to proxy the organizational input value of a PA. As a starting point and based on Governments' accounting systems, we suggest this could be built on the aggregation of the PA workforce's costs (e.g. total PA employees' salaries) or based on the PA services' costs.

Second – once a baseline for the value of a PA or public sector is obtained, this should be multiplied by the probability that such asset could be substituted or automated in a process of DX. In practice, the automatability of an entire PA or public sector would be defined as a weighted average of the automatability of all public occupations or public services.

While estimates could be based on secondary data – coming from existing estimates, or primary data – based on directly measured with experts via a survey, the automatability of jobs' tasks or services could be assessed on the basis of the above mentioned three main computation bottlenecks that can be also defined as: the intensity of cognitive or non-cognitive tasks, the level of originality, dexterity required and presence of machine-readable data.

3.2 Data sources for methodological application to the case of Italy

For illustrative purposes, we aim in this paper to adopt the above mentioned methodological framework to map out the impact from a widespread DX across the Italian PA. Such approaches, by their nature and data required, are replicable to most of other OECD countries' PA.

We summarize in Table 1 the main data sources and specific data used.

The following paragraphs describe the methods used for each of the thematic focuses.

3.3 Seizing the digital transformation impact on Italian Public Administration, based on probability of automation of public administration employees' tasks

First, we map out the DX impact on Italian PA, based on external estimates on the probability of automation of PA occupations' tasks from the latest UK Office for National Statistics report (ONS, 2019). Building up on previous methodologies, the ONS study has

Methods for estimating the DX's automation impact	Data source	Data description
Based on automatability of public occupations' tasks	ISTAT CP2001	Italian National Statistics Institute (ISTAT): Italian Labor Market occupations with ISCO codes
	MEF PA	Italian Ministry of Economy and Finance (MEF): PA occupations database
	ISCO	International Standard Classification of Occupations (ISCO) codes used to convert occupations' categories across countries
	UK ONS Labor Market statistics	UK Labor Market occupations with ISCO codes
	UK ONS Probability of Automation	Estimates on the probability of automation of UK occupations
	MEF-ISTAT labor dataset	Italian PA occupations with ISCO codes, obtained by merging MEF PA and ISTAT datasets
Based on public services' automatability	Experts panel	Estimates on the probability of automation of Italian public services based on a pool of experts' survey
	ISTAT PA	Statistics based on Italian PA public services
	MEF – ISTAT PA labor statistics	Italian PA public services and associated cost of labor

Source: Author's own elaboration

Table 1. Data sources for the analysis of DX's automation impact on public sector jobs and services

analyzed the jobs of 20 million people in the UK in 2017 and has labeled each of these occupations with a probability of automation. For example, Health and Safety Officers have a 35.8% probability of being automated, while waiters and waitresses a 72.81%.

For the application to Italian PA, we assume that such automatability effect from DX would be realized in its entirety within the next 10 years.

The time horizon of 10 years is a middle ground between ONS and OECD estimates which do not express a timeline (implicitly suggesting immediate or upcoming realization of the probability of automation) and estimates from Frey and Osborne, which indicate a time span of 10–20 years.

Once appropriately converted the 370 labels of UK to Italian occupational categories (e.g. "Top-tier executives," "Healthcare professionals") based on same international ISCO codes, these estimates were applied to the Italian PA occupations, which are detailed in the MEF (Italian Ministry of Finance) Annual Account.

Once done, to apply the UK estimates to the Italian PA occupations outlined in the MEF data set, we converted the professional categories from Italian Institute for National Statistics (ISTAT) CP2011 with the taxonomy presented by the MEF Annual Account. To enable a robust conversion and comparison, we matched each of the 109 MEF's professional categories with a group of ISTAT occupational categories based on MEF and ISTAT guidelines, and following a discussion and validation by face-to-face and electronic correspondence with experts at MEF and ISTAT. This required, for example, matching job categories based on the information provided by the account and for a similar package of complexity and nature of tasks, knowledge and experience required.

As a result, we obtained for the first time in the Italian context a new dataset with each of the PA occupations' information (e.g. salaries, number of employees in that occupation) attached to a ISCO code and an estimate on the probability of automation coming from a secondary source.

As condensed by the below equation, once obtained the probability of automation for each of the 109 PA occupations, we would be able to measure the aggregated economic value from the weighted displacement effect of DX on each of the occupations' tasks:

$$Value\ of\ the\ automation\ impact\ of\ DX\ on\ a\ PA$$
$$= \left\{€\sum PA\ occupations\right\} x\ \{\%\ PA's\ job\}$$

For the sake of illustration, if a Health and Safety Officer occupation has an annual salary of €45,000 and based on the nature of the tasks, a probability of being automated of 35.8% within the next 10 years; the value of the automatability from DX reflects the portion of tasks displaced.

The value can easily be obtained by multiplying 3.58% (given we consider a 10-year horizon) for the associated salary. The aggregated result across all the 109 professions would produce an annual estimate of the value of the DX's displacement effect.

3.4 Seizing the digital transformation impact on Italian Public Administration, based on probability of automation of public administration services

Second, we also applied our new approach to estimate the immediate DX impact on Italian PA based on the automatability of public services, and their underpinning processes.

Given the absence of current estimates produced on the DX automatability effect on services, we conducted structured questionnaires on a sample of experts to gather their estimates on the probability of automation of PA public services.

While under the first approach we estimated the value of the potential DX impact on PA by multiplying the probability of automation by occupation for the associated cost (i.e. the PA occupations' salary), under the second approach we estimate the potential DX impact's value by multiplying the probability of automation by PA public service for the associated cost to deliver the service.

Despite we do not have at this stage the break-down of costs by Italian PA public service, we used the associated cost of labor across different types of PA services e.g. "benefits, grants and loans" or "issuing authorizations." The approach can be summarized by the following formulation:

$$Value\ of\ the\ automation\ impact\ of\ DX\ on\ a\ PA$$
$$= \left\{ € \sum PA\ occupations \right\}\ x\ \{\%\ PA's\ job\ \}$$

Hence, beyond the list of public services delivered by the PA, ISTAT provided information on the % of staff involved on a specific PA activity or service ("Employed staff dedicated to direct management services/employed staff").

ISTAT grouped such statistics at aggregate level by macro-category of institutions, e.g. regions, municipalities and ministries. These statistics – in conjunction with the information on the cost of labor across several PA institutions provided by the MEF – were relevant for us to provide an initial estimate of the labor costs spent to deliver each of the 53 registered public services.

For the sake of illustration, if the public service "benefits, grants and loans" or "issue authorizations" has an annual associated labor cost to deliver it of €45m and based on the nature of the tasks, a probability of being automated of 45.5% within the next 10 years; the value of the automatability from DX reflects the portion of specific processes that can be displaced.

The value can easily be obtained by multiplying 4.55% (given we consider a 10-year horizon) for the associated production cost. The aggregated result across all the 53 types of services would produce an annual estimate of the value of the DX's displacement effect.

Following we describe more in depth the design and how we obtained these set of estimates grounded on experts' feedback, based on semi-structured questionnaires.

To identify a framework to seize the impact of DX, a content analysis method (Krippendorff, 1980; Bardin *et al.*, 2010) was applied to analyze the surveyed literature in-depth, associated to main studies such as those by Frey and Osborne (2017), Arntz *et al.* (2016) and ONS (2019).

After deciding on the purpose of the study, the first step entailed validating the correctness and completeness of such framework. To this aim, this was sent to five between academic and practical experts in Emerging Disruptive Technologies and Public Policy Innovation in the UK and Italy, who provided comments that were incorporated to refine the terminology, to make it more generalizable. These were selected based on their fit and track record on the subject as well as on their background, to make sure to include experts from the industry as well as from the government.

As a result, we could then validate the three main clusters of computation bottlenecks: extent of level of perception and manipulation, creative intelligence and social intelligence requested to deliver the mix of tasks or processes underpinning a PA job or a service.

After validation of the framework, in a second step, a questionnaire was developed asking for an estimate on the "Probability that the PA public service could be automated within next 10 years" for each of the 53 labels of public services as defined by ISTAT PA.

The questionnaire was developed alongside an explanatory note designed to provide the purpose of the study, the context and necessary background information to properly conduct the exercise. Hence, the note outlined the theoretical framework with the definition of the three bottlenecks, associated research findings and how to score for the automatability of the services.

In the note, we also outlined insights from recent ONS research studies (2019) on what words from job adverts were associated with occupation at high or low risk of automation (e.g. “machine,” “operate,” “check” versus “control” and “plan,” “research” and “advise”).

For each of the PA services, we asked for the interviewee’s view, to provide a score based on the same scale mentioned (0%–100%) once considered the presence of computation bottlenecks.

Once identified the research questions in the questionnaire and explanatory note, three experts were selected, two senior managers from a large digital technology company and from an IT strategic consultancy, and one senior manager from the UK Government expert on public programs on digital technologies.

The identification of the participants was based on their expertise as well as on their background. One common standard in defining the qualitative sample size was considering when reaching thematic saturation, which refers to the point at which no new thematic information is gathered from participants. Given the diverse background and specific competences of the interviewees as well as the number of their colleagues involved for validation, we consider at this stage – given the illustrative purposes of our framework’s application – enough information power was reached.

Once identified the interviewees, we had to consider the best ways to contact them, obtain informed consent, arrange interview times and locations. An initial contact was made through email and followed up with more details so that the individual can make an informed decision about whether they wish to be interviewed. The participants were also informed that they can refuse to answer questions or can withdraw from the study at any time, including during the interview itself.

An online conversation with each of the three experts was held to explain the purpose and the process of the exercise and helping the experts with any doubt. Ahead of the meeting, the explanatory note and the questionnaire in excel were sent by email to the pre-selected experts.

In terms of the design of the actual interview, we decided to carry out an online survey providing two weeks of time to send it back with the actual responses rather than running a face-to-face survey. The main advantages were that this allowed the respondents to take their time to study the material and provide the best answer as possible after a deep-dive research and an internal consultation. In the meantime, several interactions with the experts were conducted to clarify issues concerning concepts and completion of the questionnaire.

All these things taken into account, we considered these benefits outweighed the inherent limits from online questionaries, such as not being able to record verbal and non-verbal cues.

While our methodological approach was based on gathering information from these three experts only, we are aware that each of these respondents followed consulting and validating on the research questions in their own organization with practitioners and colleagues with a strong experience on evaluating automation technologies and their impact.

The number of practitioners reached by each expert ranged between 3 and 8; the estimates were provided following an internal consensus (at least 51% agreement).

Ultimately, as a result, each of the 3 experts returned the questionnaire with associated estimates of automatability for each of the 53 public services. For each of the estimates, experts also provided examples on how to tackle upcoming rounds of refinement of such research. Further details on the estimates from the three experts can be found in the Appendix 1 (Table A2).

We acknowledge some of the limitations this approach presents: for instance, due to the COVID-19, travel restrictions meant that it was not possible to have face-to-face interactions as initially planned and conversations with the experts and between the experts and their teams were run remotely.

Additionally, while the estimates collected by the three experts reflect the views of a much larger audience based on the size of their respective teams, we aim to further increase the scope and range of the panel of experts involved in future estimations.

4. Results

4.1 Illustrative methodological application to Italian Public Administration

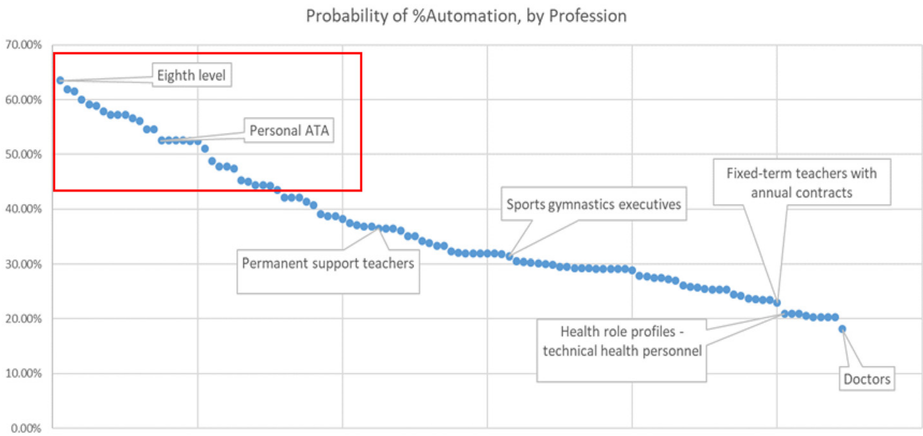
4.1.1 Seizing the digital transformation impact on Italian Public Administration, based on probability of automation of public administration employees' tasks. Matching the UK with the Italian occupational categories, we were able to use the latest ONS study estimates on the probability of automation for the Italian PA professions.

Figure 1 shows the obtained probability of automatability across PA occupations based on their tasks. We provide the granular representation of these estimates in the Appendix 1 (Table A1).

Overall, our analysis estimates an average probability of 32.3% that PA jobs within the next 10 years have the potential to be automated, once considered their underpinning tasks. Without a qualification, manual and office-based occupations tend to be the PA occupations with the highest rate of automation.

Hence, the occupations with a higher percentage of manual, administrative and routine tasks that require low competency tend to be the ones most likely to be automated within the next 10 years.

Professions such as doctors, directors and teachers tend to be the ones least likely to be automated, due to their high percentage of specialized cognitive and non-cognitive capabilities.



Source: Authors' own elaboration

Figure 1. Probability of automation by profession in the Italian PA

Once we identified the automation probability for each PA occupation category, we could seize the total absolute value of the impact from DX considering the individual automatability of each occupation based on its tasks, the salary and the volume of employees per organization.

Taking a conservative approach, assuming that the value of the impact should be proportionate to how widespread is the level of DX technologies adoption – we identified a baseline value of annual displacements in the PA in the next 10 year for €3.45bn. It is worth flagging how these potential "time/cost savings" estimates are associated to the actual widespread uptake of digital technologies. A successful scale up of DX technologies would depend by multiple exogenous and controllable factors such as the ability of the PA's change management to implement the right enablers and delivery mechanisms to maximize DX opportunities.

That said, as it is possible to see in Figure 2, in absolute terms the greatest automation opportunities come from those occupations in the PA which have a high intensity of administrative and machine-readable routine tasks. These include civil servant and public servant roles such as Categories C and D and Areas A and B as well as "Assistants" and "Personal A.T.A." (school non-teaching staff).

4.1.2 Seizing the digital transformation impact on Italian Public Administration, based on probability of automation of public administration services. Based on the methodological framework mentioned and primary data, with estimates from a pool of industry and academic experts, we could then estimate the automatability for each PA's public service, and whether these might be more or less likely objects of automation within a widespread DX.

As mentioned above, first, we estimated the total value of PA public services, based on the labor costs allocated to each public service.

Applying previously mentioned methodology and experts' assessment on the probability of automation, we were able then to map out low, medium and high automatable public services, and consequently, the associated value of processes displaced from automation with DX.

Based on this second methodological strand, based on the probability of automation of PA public services, overall our analysis estimates the baseline annual value of displacement in the PA for €3.05bn over the next 10 years. This value does not differ significantly from previous estimations based on the probability of automation of occupations.

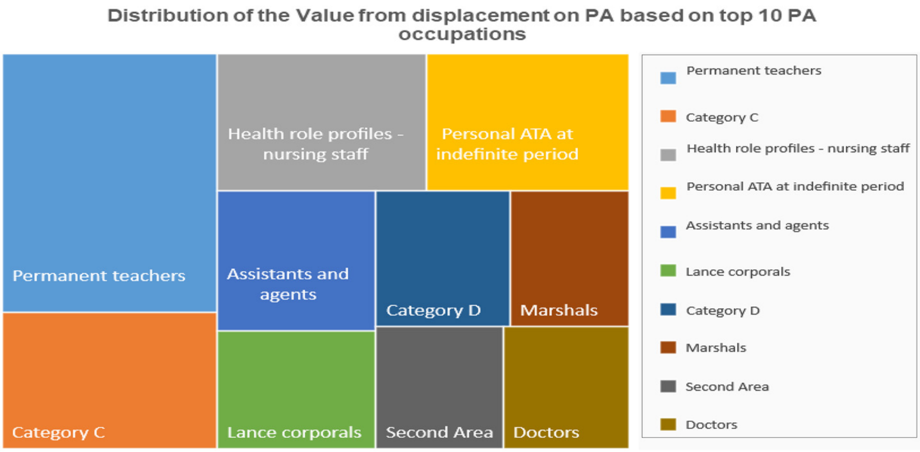


Figure 2. Value of the impact from digital transformation considering the individual % automatability of each occupation based on its tasks, the salary and the volume of employees per organization in the Italian PA

Source: Authors' own elaboration

As shown in Figure 3, results suggest the highest impact from DX automation effects to come for transactional activities such as copy of judicial documents, issuing authorizations and certifications and other administrative office activities.

The PA public services that would involve a high intensity of dexterity, original tasks and that require sophisticated cognitive capacities would tend to be less automatable. These include, for example, PA public services such as "activities of nurses and physiotherapists (other human health activities)" or "teaching activities (tertiary education: graduate or post-graduate level; arts schools)."

On the other hand, public services can be defined as *highly automatable* when these involve a low level of cognitive (such as judgment and computation) and non-cognitive (such as caring) skills, and when these involve mostly repetitive, manual and machine-readable tasks.

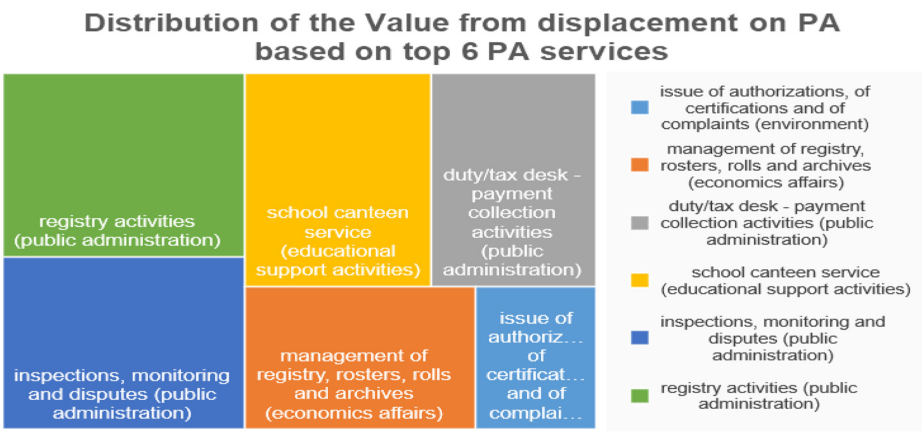
These include for example, PA public services such as "copy of judicial documents (law and justice)" and "issue of authorizations, of statements, of certifications and of appraisals (law and justice)."

5. Discussion and policy implications

The application of our novel methodological framework to the Italian PA highlights how this could hand over to public managers a useful tool to anticipate and map out the potential impacts and risks from a widespread uptake of digital technologies across a public organization. This framework would become more and more valuable in contexts where primary data are not available, and more generally in a data-constrained environment.

The underpinning framework is replicable, and the same approach could be applied to other countries' PA. In terms of next iterations, we aim to enhance our framework to ensure a more granular and detailed distributional analysis and map out the DX impact across the PA also by type of organization and across geographies.

In relation to the mentioned limitations of our methodology, the work could certainly be improved in terms of the robustness of the estimates obtained on the DX *automation* effect, relying on a broader pool of experts and triangulating the results with emerging bottom-up evidence. Furthermore, we are conscious the paper applies estimations based on a different context to the Italian sector and does not factor in the cost of new technologies in the



Source: Authors' own elaboration

Figure 3. Value of DX impact on PA public services, based on the labor costs allocated to each public service in the Italian PA

projections provided. These limitations could be addressed in future versions of the paper, with a wider level of data availability.

This new methodological approach would also enable to look for the first time at the distributional impact of digital technologies across the PA workforce and on how automatability would relate with the average salaries.

As shown in Figure 4, carrying out a correlation analysis, initial results seem to show a *negative* relationship with a Bravais–Pearson correlation coefficient of −0,52, suggesting that on average PA employees that have a lower salary tend to have more automatable tasks, leading to relevant consequences in terms of policy implications.

That said, further iterations of this approach could be aimed to strengthen and test these insights carrying out a more comprehensive econometric analysis to test the statistical significance between these variables, and appropriately treat factors affecting causation such as the endogeneity problem.

More generally, we consider that these and previous results should be interpreted with caution. As suggested by Arntz *et al.* (2016), the methodological approach on estimating the displacement impact from DX based on its automation effect, still reflects technological capabilities rather than the actual utilization of such technologies, which might lead to a further overestimation of the occupation automatability. For this reason, we attempted mitigating these by spreading the opportunities over a longer period of time.

In addition, even if the new DX technologies are increasingly adopted across the PA, the prospects of task substitution depend on whether PA workplaces adjust to a new division of labor, as workers may increasingly perform tasks that are complementary to new technologies.

Other limitations include that our approach considers only existing jobs, although new digital technologies are likely to create new jobs and associated tasks.

All these things considered, the study reinforces, in line with extant literature (Adamczyk *et al.*, 2021; Arntz *et al.*, 2016) how low educated workers across the PA likely will bear the

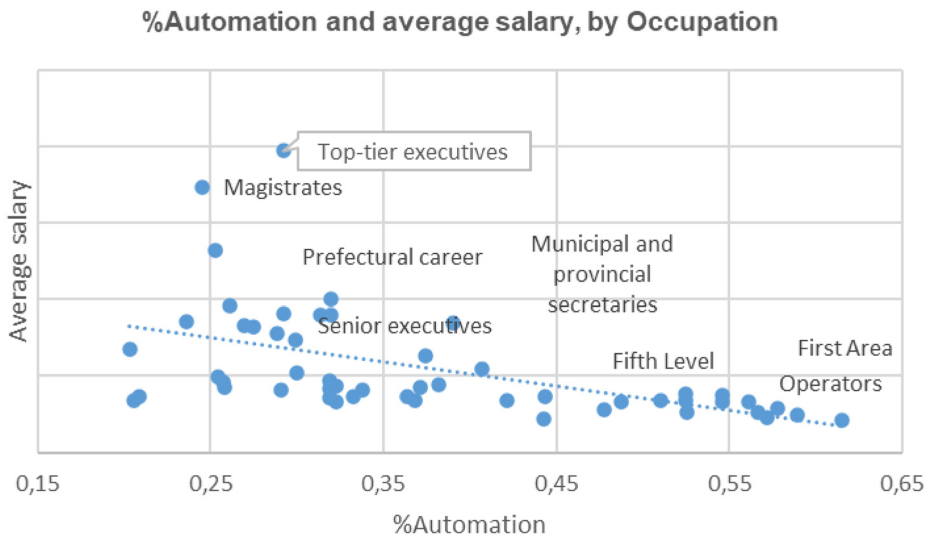


Figure 4.
Distributional impact of digital technologies across workforce in the Italian PA

Source: Authors' own elaboration

impact of adjustment costs to technological change, in terms of requirements for further training and occupational retraining. For this group of workers, regaining the competitive advantage over new digital technologies by means of upskilling and training may be difficult to achieve, especially as the speed of the current 4.0 technological revolution appears to exceed the pace of its predecessors.

These findings point toward the need to focus more on the potential inequalities and requirement for the re-training arising from technological change and on how public management would be able to rely on DX to ensure inclusive income growth, i.e. reducing the gap between high and low salaries across the public sector through higher labor productivity boosted by DX.

Furthermore, this framework could assist policymakers' choices on public employment. By enabling informed, data-driven analysis on the professions and services most exposed to automatability, such analyses could help singling out areas which are more prone to substitution or complementarity, thus informing the prioritization of workers' profiles and competences to be included in recruitment processes.

6. Conclusions

Based on lessons learned from close disciplines, such as economics and automation engineering, our paper proposes a new framework for policymakers and public managers to disentangle and measure the impact from digital technologies uptake on the public sector.

Building on this, our paper suggests a new and replicable framework for public managers to measure the value and risks from DX investment on PA, which are adopted in part from existing best practices in other disciplines and applied originally to a public management setting.

The new framework for policymakers estimates the economic *value* of the *automation* impact of DX on the public sector using the total earnings of public employees and the total costs of public services.

Having caveated the assumptions and its limitations, these new tools would be ultimately useful as a basis for policymakers and public manager to make more targeted evidence-based DX investments' decisions in a data-constrained environment, and to better target new public policies to support digital inclusion, such as training and re-skilling, and recruitment.

For illustrative purposes, applying the new approach to the Italian PA, our analysis highlighted initial findings on the overall value of the impact on PA as a whole and by type of PA profession and by PA service.

Results show a strong expected impact from DX on Italian PA revealing the sign and the magnitude of promises of efficiency gains as well as raising concerns in terms of potential risks of job displacement and of arising income inequality across the PA workforce. Further applications of this framework could vertically target specific service chains or geographical clusters, to provide more qualitative and nuanced evidence on the automation/augmentation tradeoff and the associated change management challenges in specific administrative settings.

References

Adamczyk, W.B., Monasterio, L. and Fochezatto, A. (2021), "Automation in the future of public sector employment: the case of Brazilian Federal Government", *Technology in Society*, Vol. 67, p. 101722.

Alon-Barkat, S. and Busuioc, M. (2023), "Human–AI interactions in public sector decision making: "automation bias" and "selective adherence" to algorithmic advice", *Journal of Public Administration Research and Theory*, Vol. 33 No. 1, pp. 153-169.

Andersson, C., Hallin, A. and Ivory, C. (2022), "Unpacking the digitalisation of public services: Configuring work during automation in local government", *Government Information Quarterly*, Vol. 39 No. 1, p. 101662.

Arntz, M., Gregory, T. and Zierahn, U. (2016), "The risk of automation for jobs in OECD countries: a comparative analysis", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris;

Bardin, J., Lalanda, P. and Escoffier, C. (2010), "Towards an automatic integration of heterogeneous services and devices", *2010 IEEE Asia-Pacific Services Computing Conference*, *Hangzhou, China*, pp. 171-178.

Berghaus, S. and Back, A. (2016), "Stages in digital business transformation: results of an empirical maturity study", *MCIS 2016 Proceedings*. 22.

Borry, E.L. and Getha-Taylor, H. (2019), "Automation in the public sector: efficiency at the expense of equity?", *Public Integrity*, Vol. 21 No. 1, pp. 6-21.

Brown, M.M. (2001), "The benefits and costs of information technology innovations: an empirical assessment of a local government agency", *Public Performance and Management Review*, Vol. 24 No. 4, pp. 351-366.

Brynjolfsson, E. and McAfee, A. (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, WW Norton and Company, New York.

Campion, A., Gasco-Hernandez, M., Jankin Mikhaylov, S. and Esteve, M. (2022), "Overcoming the challenges of collaboratively adopting artificial intelligence in the public sector", *Social Science Computer Review*, Vol. 40 No. 2, pp. 462-477.

Carbo, T. and Williams, J.G. (2004), "Models and metrics for evaluating local electronic government systems and services", *Electronic Journal of E-Government*, Vol. 2 No. 2, pp. 95-104.

Cooper, L.A., Holderness, D.K., Jr, Sorensen, T.L. and Wood, D.A. (2019), "Robotic process automation in public accounting", *Accounting Horizons*, Vol. 33 No. 4, pp. 15-35.

Davenport, T.H. and Kirby, J. (2016), "Just how smart are smart machines?", *MIT Sloan Management Review*, Vol. 57 No. 3, pp. 21-25.

Daugherty, P.R. and Wilson, H.J. (2018), *Human + Machine: Reimagining Work in the Age of AI*, Harvard Business Review Press, Boston.

de Boer, N. and Raaphorst, N. (2023), "Automation and discretion: explaining the effect of automation on how street-level bureaucrats enforce", *Public Management Review*, Vol. 25 No. 1, pp. 42-62.

de Sousa, W.G., de Melo, E.R.P., Bermejo, P.H.D.S., Farias, R.A.S. and Gomes, A.O. (2019), "How and where is artificial intelligence in the public sector going? A literature review and research agenda", *Government Information Quarterly*, Vol. 36 No. 4, p. 101392.

Esteves, J. and Joseph, R.C. (2008), "A comprehensive framework for the assessment of eGovernment projects", *Government Information Quarterly*, Vol. 25 No. 1, pp. 118-132.

Frey, C.B. and Osborne, M. (2017), "The future of employment: how susceptible are jobs to computerisation?", *Technological Forecasting and Social Change*, Vol. 114, pp. 254-280.

Kaplan, A. and Haenlein, M. (2020), "Rulers of the world, unite! the challenges and opportunities of artificial intelligence", *Business Horizons*, Vol. 63 No. 1, pp. 37-50.

Krippendorff, K. (1980), "Validity in content analysis", In E. Mochmann (Ed.), *Computerstrategien für Die Kommunikationsanalyse*, Campus, Frankfurt/New York, pp. 69-112.

Kunstelj, M. and Vintar, M. (2004), "Evaluating the progress of eGovernment development: a critical analysis", *Information Polity*, Vol. 9 Nos 3/4, pp. 131-148.

Kuziemski, M. and Misuraca, G. (2020), "AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings", *Telecommunications Policy*, Vol. 44 No. 6, p. 101976.

Lee, G. and Perry, J.L. (2002), "Are computers boosting productivity? A test of the paradox in state governments", *Journal of Public Administration Research and Theory*, Vol. 12 No. 1, pp. 77-103.

Luna-Reyes, L.F., Gil-Garcia, J.R. and Romero, G. (2012), "Towards a multidimensional model for evaluating electronic government: Proposing a more comprehensive and integrative perspective", *Government Information Quarterly*, Vol. 29 No. 3, pp. 324-334.

Moon, M.J. and Norris, D. (2005), "Does managerial orientation matter? The adoption of reinventing government and e-Government at the municipal level", *Information Systems Journal*, Vol. 15 No. 1, pp. 43-60.

Neumann, O., Guirguis, K. and Steiner, R. (2022), "Exploring artificial intelligence adoption in public organizations: a comparative case study", *Public Management Review*, pp. 1-27.

OECD (2003), "The e-government imperative", *OECD e-Government Studies*, OECD Publishing, Paris.

OECD (2020), "Building capacity for Evidence-Informed Policy-Making: Lessons from country experiences", *OECD Public Governance Reviews*, OECD Publishing, Paris.

Office for National Statistics (2019), "The probability of automation in England: 2011 and 2017", available at: www.ons.gov.uk/

Raisch, S. and Krakowski, S. (2021), "Artificial intelligence and management: the automation–augmentation paradox", *Academy of Management Review*, Vol. 46 No. 1, pp. 192-210.

Vial, G. (2019), "Understanding digital transformation: a review and a research agenda", *The Journal of Strategic Information Systems*, Vol. 28 No. 2, pp. 118-144.

Willems, J., Schmid, M.J., Vanderelst, D., Vogel, D. and Ebinger, F. (2022), "AI-driven public services and the privacy paradox: do citizens really care about their privacy?", *Public Management Review*, pp. 1-19.

Appendix. Automatability across Italian PA occupations

PA occupation (MEF label)	Average automation probability (%)
Eighth level	63.47
Category PLS	61.94
Category A	61.52
Category FA	60.03
Area A	59.17
First Area	58.90
Seventh Level	57.81
Fixed-term area personnel annual contract	57.18
Fixed-term area personnel annual contract till the end of teaching activity	57.18
Fixed-term area personnel	57.18
Operators	56.62
Technical-information officials	56.09
Sixth level	54.59
Lance corporals	54.59
Personal ATA (schools' non-teaching staff)	52.52
Personal ATA at indefinite period	52.52
Personal ATA at indefinite period with annual and non-annual contract	52.52
Personal ATA with a contract until the end of the didactic activity	52.52
Assistants and agents	52.45
Assistants	52.45
Collaborators and deputy technical-IT directors	51.02
Collaborators and substitute administrative-contracting directors	48.77
Second Area	47.76
Area B	47.76
Non-executive personnel	47.33
Profiles health role-staff rehabilitation functions	45.21
Administrative role profiles	45.04
Remaining staff	44.43
Fifth Level	44.31
Category B	44.29
Category C	43.52
Category PLA	42.15
Category FB	42.15
Accounting administrative officers	42.13
Role profiles health-personnel supervision and inspection	41.36
Sports gymnastic directors	40.70
Municipal and provincial secretaries	39.05
Category PLC	38.75
Category FC	38.75
Superintendents	38.19
Directives	37.46
Fourth level	37.12
Third area special non-contractual organizational positions	36.80
Third area	36.80
Permanent support teachers	36.39
Temporary support teachers with an annual contract	36.39
Support teachers with a contract until the end of the teaching activity	36.39

(*continued*)

Table A1.
Probability of automation by occupation category, Italian PA

PA occupation (MEF label)	Average automation probability (%)
Category D	36.00
Area C	35.06
High specializations in D.O.	35.06
Category EP	34.13
Medical directors	33.81
Fire fighters	33.28
Vigilantes	33.28
Brigadiers	32.30
Contractor staff	32.05
Diplomatic career	31.96
Prefectural career	31.96
Graduated	31.91
Marshals	31.91
Sergeants	31.91
Profile professional roles	31.83
Sports gymnastics executives	31.35
Executives and high specializations outside the organization	30.55
Health role profiles – nursing staff	30.34
Troop soldiers	30.27
Managers technical role	30.15
Lower officers	30.01
Senior executives	29.91
Category PLB	29.47
Non-medical health-care executives	29.46
Top-tier executives	29.21
Second-tier executives	29.21
General managers	29.21
Second qualification professionals	29.18
First qualification professionals	29.18
High personal professionalism – fixed term	29.08
High professionalism staff	29.08
High personal professionalism determined time annual contracts	29.08
Health-care professionals (Ministry of Health)	28.84
Managers professional role	27.87
Managers administrative role	27.71
Senior officers	27.47
Directors	27.44
Technologists	27.27
Medical executives	26.98
School leaders	26.14
Researchers	25.79
Inspectors and replaced directors	25.74
Inspectors	25.46
Collaboration area	25.36
Professionals	25.35
General officers	25.30
Magistrates	24.49
Dentists	24.18
Teachers	23.73
Prison career	23.62
Veterinarians	23.50

(*continued*)

Table A1.

PA occupation (MEF label)	Average automation probability (%)
Fixed-term teachers with annual and non-annual contracts	23.49
Fixed-term teachers with annual contracts	23.01
Health role profiles – technical health personnel	20.99
Technical role profiles	20.99
Permanent teachers	20.91
Permanent religion teachers	20.61
Temporary professors until the end of teaching activities	20.34
Fixed-term professors with annual contracts	20.34
Professors	20.34
Professors in charge	20.34
Doctors	18.11

Table A1.

Source: Authors' elaboration based on ISTAT PA and MEF data set

Automatability across Italian PA services

Public service	% Automatability Expert 1	Expert 2	Expert 3
Activities of medical laboratories: X-ray laboratories, blood analysis laboratories; blood, sperm and transplant organ banks (other human health activities)	30	30	30
Activities of nurses and physiotherapists (other human health activities)	30	0	30
Administrative office: external relations and communication (administrative activities of providing education)	70	30	70
Animal medicine (other human health activities)	30	0	30
Archive activities (arts activities)	30	30	30
Benefits, grants and loans (agriculture)	70	30	70
Benefits, grants and loans (commerce and craft affairs)	70	30	70
Benefits, grants and loans (labor and social affairs)	70	30	70
Copy of judicial documents (law and justice)	70	70	70
cup – health multifunctional center (administrative activities in health care)	70	70	70
Duty/tax desk – payment collection activities (public administration)	70	70	70
Emergency medicine (hospital activities)	0	0	30
External relations and citizen communication (administrative activities in health care)	30	30	70
External relations and citizen communication (public administration)	30	30	70
General medicine (medical consulting activities)	30	0	30
Help desk and center of employment (labor and social affairs)	70	30	70
Hospital pharmacy management (hospital activities)	0	0	30
Inspections, monitoring and disputes (public administration)	30	30	70
Inspections, monitoring and issue of opinions (commerce and craft affairs)	70	0	70
Inspections, monitoring and issue of opinions (infrastructures and transport)	70	0	70
Issue of authorizations, of certifications and of complaints (commerce and craft affairs)	70	70	70
Issue of authorizations, of certifications and of complaints (economics affairs)	70	70	70
Issue of authorizations, of certifications and of complaints (environment)	70	70	70
Issue of authorizations, of certifications and of complaints (infrastructures and transport)	70	70	70
Issue of authorizations, of certifications and of complaints (public administration)	70	70	70
Issue of authorizations, of certifications and of complaints (real estate)	70	70	70
Issue of authorizations, of statements, of certifications and of appraisals (law and justice)	70	70	70
Judgments, order to pay and opinions (law and justice)	0	0	30
Judicial sales and writs of execution (law and justice)	30	0	30
Legal medicine (administrative activities in health care)	30	0	70
Library activities (arts activities)	30	30	30
Management and conservation of historical and artistic heritage (cultural activities)	30	0	30
Management of botanical, zoological gardens and nature reserves (cultural activities)	30	0	30
Management of registry, rosters, rolls and archives (economics affairs)	70	30	70
Management of sports facilities and recreation activities (sports activities)	0	0	30

(*continued*)

Table A2. Probability of automation of public services for Italian PA: resume of experts' estimates

Public service	% Automatability Expert 1	Expert 2	Expert 3
Museum activities (arts activities)	30	0	30
Other social work activities without accommodation	30	0	30
Placement (educational support activities)	0	0	30
Professional practice examination (economics affairs)	30	0	30
Registration, medical reports and medical archive consultation (administrative activities in health care)	30	70	70
Registry activities (administrative activities in health care)	70	70	70
Registry activities (commerce and craft affairs)	70	70	70
Registry activities (public administration)	30	70	70
School canteen service (educational support activities)	70	30	70
Specialized medicine (medical consulting activities)	30	0	30
Specialized treatments (hospital activities)	30	0	30
Student administrative office (administrative activities in education)	70	70	70
Surgery (hospital activities)	30	0	30
Tax roll (law and justice)	70	30	70
Teaching activities (tertiary education: graduate or post-graduate level; arts schools)	0	0	30
Tourist hospitality and tourism management (tourism)	30	0	70
Training activities (other education)	30	0	30
Training activities (tertiary education: graduate or post-graduate level; arts schools)	30	0	30

Table A2.

Source: Authors' and experts elaboration based on ISTAT PA and MEF occupational classifications

Corresponding author
Andrea Bonomi Savignon can be contacted at: bonomi.savignon@economia.uniroma2.it