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Training in Digital Skills—The Perspective of Workers in Public Sector

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Abstract: Digital transformation can become a complex process when workers have insufficient skills, which makes training in the digital field essential. Herein, we intend to relate the digital literacy perceived by workers with their training needs for the Portuguese public sector context. Additionally, based on the Human capital theory, we also investigate which professional/demographic characteristics increase training propensity in digital fields. Through an online questionnaire, a dataset with information on 573 workers was obtained. The data analysis was made by using a probabilistic regression model and additional statistical techniques. The results revealed that workers with higher levels of education and higher professional skills have higher probability of participating in training in the digital field. On average, workers reveal low levels of digital knowledge (2.7 in a 1–5 scale) and low participation in training in the digital fields (72% of the sample had no training over the last two years), but the majority present a willingness to participate in future training sessions, especially in the fields of Dataset management, Cybersecurity and Communication systems. This study provides information on training in the digital field of public workers, which is essential for public organizations to better prepare for digital transformation. Additionally, it contributes to a very recent literature on digital learning, and it can be extended to other contexts.

Keywords: digital transformation; digital competences; professional training; public services; human capital

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1. Introduction

Digital transformation is currently ongoing with an increased pace, particularly since the COVID-19 pandemic, during which citizens and organizations were forced to accelerate digital technologies' adoption and integration [1,2]. Such a rapid change requires all organizations to adapt the way they operate and deliver value to customers. This is obviously also the case of the public sector, in which organizations intend to take advantage of the full potential of digital technologies in order to become more modernized and closer to the needs of citizens [3,4]. This endeavor is a very demanding one, since public services are constantly being challenged to improve service delivery. Less bureaucracy and more openness in interactions, timely and responsible manners and minimizing administrative costs, which are financed by citizens' taxes, are desirable.

Digital transformation in the public sector, however, can become slow and complex when workers lack some skills. Considering that formal education takes too long to adapt curricula and, afterwards, to provide the labor force with digitally-skilled workers, training the active population and, particularly workers in the public sector, is paramount in addressing the digital skills' shortage [5]. In fact, through training, organizations are able to empower workers with the desired skills and knowledge which will contribute to reinforce productivity [4,6]. Moreover, ensuring lifelong learning opportunities for workers through professional training is essential in order contribute to the achievement of Sustainable

Development Goals (SDG), such as the SDG4—Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all, and the SDG8—Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all [7]. Additionally, and according to the endogenous growth theory developed, for example by Robert Lucas [8], physical capital, human capital and technology are complementary, which means that the effect of technologic advances (such as those related with digital transformation) on productivity and growth is leveraged when accompanied by the reinforcement of physical resources as well as the adequate reskilling of human resources. Considering that the Portuguese active population has been decreasing over the last decade, the complementarity between digital training and technology assumes, for the Portuguese context, an even greater relevance that is essential for economic growth and sustainable development.

Being aware of these challenges, the European Council and the Commission have defined digital transformation as a strategic path to guide Europe's development in the upcoming years. Accordingly, planned investments and reforms under the Recovery and Resilience Facility dedicate 46 billion euros to the area of the digitalization of public services and government processes [2]. In Portugal, the national context of the present study, the Recovery and Resilience Plan (RRP) defined a specific component related to Empowerment, Digitization, Interoperability and Cybersecurity in public administration, with a foreseen investment amount of 578 million euros, of which 86 million euros are dedicated to public servants' training and capacity building [9].

Considering the increased political relevance attributed to digital transformation and training in the public sector, studies that contribute to helping organizations understand the major digital needs and who tends to participate more in professional training in the digital field are essential for facilitation and making the process of digital transformation more efficient.

In such context, the main goal of this research is to investigate, in the Portuguese public sector, which professional and demographic characteristics are related with the attendance of professional training in general and, particularly, in the digital field. Additionally, we aim to relate the level of public sector workers' digital competencies with their perceived training needs in digital tools. Finally, and considering the importance of workers' motivation to participate in training, it is also a purpose of this work to identify the main benefits of training from the participants' perspective.

This paper relies on the human capital theoretical framework, namely the seminal works of Becker [10] and Mincer [11], to empirically study the training incidence and perceived benefits (from the workers' perspective). In spite of the consolidated literature concerning training incidence determinants, for instance in [12–19], the application of it to the specific fields of the public sector and of the training in digital skills has been somewhat neglected. Additionally, although there is an increasing amount of literature devoted to the importance of digital transformation in the public sector, with recent examples such as [1,20,21], the majority of studies has tended to rely mainly on case studies, analyzing their processes and implementation success factors, without paying sufficient attention to the crucial role of workers' training on those processes. Recently published systematic literature reviews covering the theme of digital transformation in the public sector make it evident that the specific topic of workers' training has been overlooked [3,22,23]. Hence, this paper intends to address this literature gap, developing a study on training incidence and training benefits, with a particular approach to digital training, and applying it to the specific context of the public sector.

The adopted methodology consisted of a quantitative approach, using primary data. The instrument used to collect the data was the survey by questionnaire, available on several online platforms. A total of 618 responses were obtained, of which 573 were considered complete and therefore validated. Based on the human capital theory, a probabilistic regression model was used to relate several workers' and job characteristics, such as education, age, marital status, parenthood, job tenure, professional qualification, type of

professional contract and subsector, with the likelihood to participate in training in digital and non-digital fields.

The paper is organized in the following way: after this introduction, previous theoretical and empirical contributions on this topic are reviewed. The third section presents the data collection instrument and the model specification. Next, the results obtained from models' estimations and statistics related with digital skills, training needs and training benefits are presented, interpreted and related to previous studies. The last section closes the paper, discussing the obtained results, referring to limitations of the work and suggesting future research directions.

2. Theoretical Framework and Research Hypotheses

The term digital transformation in public sector is generally understood as a strategic mechanism of change which, through the use of digital technologies, allows the public administration to improve interactions with users, leading to a more efficient and effective public service, with a higher value creation for citizens and organizations [1,3,24]. Digital transformation is currently an endeavor for governments all over the world, who try to keep up with the tremendously fast development of new information and communication technologies, and are moved by several motives: improve efficiency in resource use and service quality; increase users' access, inclusion and participation; enhance accountability and transparency; and, through delivering a better service, improve the governments' image and public trust [21,22,25]. The principle of user-centered digital services—putting the needs of citizens and organizations at the heart of public sector reforms—is the main element that characterizes the paradigm shift that has been occurring from the earlier stages of the e-government—mere online presence, provision of information, online interactions and transactions—to digital transformation [19,24].

In spite of the numerous programs implemented by governments worldwide to boost progress towards digital transformation, according to the Digital Economy and Society Index (DESI) produced by the European Commission, progress has been uneven across European Union (EU) countries and "services for citizens are less likely to be available online when compared to services for businesses" [2] (p. 3). DESI is a composite index which accounts for five sub-dimensions within the dimension of digital public services: (i) e-government users, measuring the percentage of internet users that use it to interact with the public services; (ii) availability of pre-filled forms, following the "once only" principle; (iii) digital public services for citizens, provided online, through a government portal; (iv) digital public services for businesses, measuring the degree to which those services are interoperable and work cross-border and (v) the government's commitment to open data policy. In 2021, Portugal ranked in the 14th position, scoring 67.9/100 and aligned with the EU average. Such an overall score is due to the fact that Portugal scores slightly above the EU average in all sub-dimensions, except in the one related to open data, in which the Portuguese score is the fifth worst among European countries [2].

The Portuguese government has implemented several programs designed to improve the digitalization of public services, which recently received an investment boost related to the implementation of the national RRP. In this context, the specific capacity building program "AP Digital 4.0" (AP stands for Public Administration (*Administração Pública*)) should be highlighted, since it is specifically designed to train public sector workers and leaders for digital transformation, based on the understanding of emerging technologies, such as the management of big data, algorithms, digital innovation, robotics, artificial intelligence and cybersecurity, and it aims to train over 60,000 public servants by 2025 [26]. However, more basic competencies concerning the established information and communication technologies might also be lacking in public sector workers, justifying a general approach to capacity building, in order to narrow the gap between existing and needed digital competencies. The Citizens' Digital Competence Framework, known as DigComp (updated in 2022), identifies key areas of digital competence, serving as a reference for EU-wide policymakers in this field of building digital competences through education and

training initiatives. In this framework, digital competencies are grouped into five areas: Information and data literacy; communication and collaboration; digital content creation; safety; problem solving. Each competence area is then broken down into more specific competencies [27]. This European framework, complemented by the recent literature review provided by [28] along with experts' consultation, was used to define the digital competencies used in this study.

According to the human capital theory, the decision of investing in human capital—either through formal education or training—is made when the present value of future expected benefits exceeds the current (direct and opportunity) costs associated to that investment [10]. In the case of training, and when it is from the organization's initiative, costs include those directly related with training provision and the foregone productivity associated with on-the-job hours spend in training sessions; the benefits are mainly related to future workers' productivity gains. From the employee perspective, the assessment of benefits is concerned with the expected consequences of training skills attainment on wages and career development prospects [17]. Previous literature generally points out that the benefits outweigh the costs (in [29], for example, positive internal rates of return were obtained for both organizations and workers) which leads to the training offered and participation. However, the expected benefits and costs of training might depend on worker and job characteristics. Thus, the probability of participating in professional training may be unevenly distributed across different groups of workers.

Regarding the influence of individual attributes on training incidence, the education level assumes a prominent role. The likelihood to participate in training has been positively related to the worker's level of schooling by a vast number of empirical studies [12,13,30–32]. This relationship, supported by the human capital theory, relies on the argument that workers who have a greater learning capacity may be able to make better use of the knowledge taught (absorptive capacity), increasing the efficiency of training [11,12,33]. In fact, formal education is viewed as "a complementary factor of training at work in the production of human capital" [11] (p. 10), with this complementarity being associated with the achievement of higher levels of productivity.

Although the dominant literature corroborates a positive relationship between education level and training incidence, past findings are not completely consensual. For instance, a negative relationship between education level and training was obtained in [16,19]. The former authors justify their results, arguing that, when the decision is made autonomously by the worker, the expected marginal benefits (in terms of wage differential or career prospects) will be higher in the case of workers with less formal education, while the latter claims that this negative relation occurs because firms use workplace training to close the gap between the competencies needed for the job and the ones already attained by the worker. Nevertheless, in this research we followed the majority of the literature in establishing our hypothesis of a positive relationship between education level and training. We recognize, however, that the current context is extremely distinct from what it was years ago: skills requirements, particularly digital skills, are changing at a much quicker pace than before, thus justifying new studies to confirm (or not) previous results.

Moreover, qualification level or occupational category has been proven to influence training participation, as higher ranked qualification levels may require more demanding competencies and skills [17]. The authors of [16] demonstrate that the likelihood of participating in non-mandatory training is higher for workers holding a higher hierarchical position. Accordingly, Georgellis and Lange [30] find that training participation is higher in more skilled workers, this being applicable to the public sector. In their recent study, the authors of [5] conclude that workers with higher qualification levels ("white-collar" as opposed to "blue collar") present a higher probability of receiving training.

Supported by the previous arguments, we hereby establish the following hypotheses:

Hypothesis 1a: *Professional training incidence is positively related with workers' education level.*

Hypothesis 1b: *Professional training incidence is positively related with workers' professional qualification*.

Similar arguments associated to the human capital model have been put forward to negatively associate the worker's age and/or job tenure with professional training participation [13]. According to the authors of [10], it is expected that younger professionals receive more on-the-job training than older people, since the return on investment is higher the longer the worker is expected to stay in the company. In developed countries, that are dramatically recording an ageing active population, this potential negative effect of age is certainly worrying, since it may inhibit the necessary upskilling and reskilling of workers, particularly in the face of digital transformation processes [34]. The negative impact of age on training incidence has been confirmed by several empirical studies (e.g., [19], analyzing participation in employer-sponsored training, and [16,18], applied to non-mandatory training). The study of [5] also supports this negative effect of age, which holds even after including variables that control for workplace features. A slightly different result was found in [30], where an inverse U-shaped relationship between age and training participation was identified, meaning that in earlier ages the participation is lower, increasing after a few years of job experience and decreasing in older workers. In the study of [13], age and job tenure are both used as potential explanatory variables of training participation, among other employee and employer characteristics, concluding that the influence of age is not statistically significant; yet, job tenure is found to have a significant and negative effect. Age and job tenure were both considered in [35], evidencing that, in the case of the public sector, age does not have a significant effect, while job tenure has a significant and negative influence in training propensity.

Based on the above, the following research hypotheses are established that intend to separately test the effect of age and job tenure:

Hypothesis 2a: *Professional training incidence is negatively related with workers' age*.

Hypothesis 2b: *Professional training incidence is negatively related with the job tenure of the worker*.

The study upon the influence of gender in training incidence can also be framed within the human capital model, under the argument that it is not gender, per se, that determines the propensity to engage in training initiatives (either employer or employee-sponsored), but rather the degree of job attachment and expected tenure [36]. Under such an argument, and considering the still existing gender discrimination concerning family care responsibilities, it could be expected that females are more subject to job interruptions, thus decreasing the likelihood of both employers and female employees themselves to invest in training efforts [15]. Another possible explanation relies on the gender segmentation that prevails in labor markets: more demanding occupations and industries in terms of continuous upskilling (i.e., technological-related) tend to be held mostly by men, hence justifying a higher participation of males in job-related training [16]. These arguments support the findings of empirical studies that negatively relate female gender with training incidence, such as [14,30]. However, when other variables, such as professional qualification, businesses sectors and parenthood, are included in the model, different results may be found.

Some authors have concluded an opposite influence of gender on training incidence. According to the authors of [37], the circumstance of frequent job breaks that affect more women may actually inspire them to use work-related training opportunities to catch up and close the skills' gap. The research, developed by [25], was applied to public administration workers in Czeck Republic and concludes that men self-assess their soft skills and professional competences at a higher level than women; this may act as a motivating factor for women to participate more in training. In the study carried out by [38], women demonstrate a higher attendance of training sessions than men and have generally more

positive attitudes towards training. The author explains this relationship by considering that "training is more beneficial due to the technical nature of the work functions that are being placed on women (who may not feel prepared for these functions)" [38] (p. 9). The authors of [16] also found that women are more likely than men to participate in non-mandatory training. Similar results were found in [15], even controlling for other employer and employee features. The authors of [5] also test for the influence of gender on the likelihood of receiving training, but the results for this variable were not statistically significant.

Hence, the following hypothesis is established for empirical testing:

Hypothesis 3: *Professional training incidence is determined by gender, as it is higher in female workers than in men*.

Work stability also has a potential influence on training incidence. Organizations are more willing to invest in the training of workers with longer employment contracts, since they guarantee a greater return than the investment made in workers with temporary contracts. The predisposition of workers or organizations to bear training costs is intertwined with the likelihood of labor turnover [10]. From the perspective of Mincer [11], workers who receive training in the workplace are those who have lower turnover rates, since training aimed at increasing the skill and productivity rates of an organization is not fully applicable in other organizations. For this reason, it is expected that workers with more precarious contractual ties, and therefore with a higher turnover rate, have less training than the remaining [17]. This theoretical rational has been tested empirically in studies such as [16,19], who posit that full-time employees are more prone to participate in training than part-time employees. However, results obtained in those studies did not fully corroborated this hypothesis. In their research comparing the public sector with the private sector regarding training incidence, the authors of [35] validate the positive influence of permanent contracts in both sectors.

Hypothesis 4: *Professional training incidence is positively influenced by labor contract stability of workers*.

Although there is much literature relating individual characteristics with training propensity, little is known about this relationship for the specific case of training in the digital field. Thus, we aim to contribute to the emerging literature on digital learning, by testing the abovementioned hypotheses in both cases of training in digital and non-digital fields, through the conceptual model presented in Figure 1. Additionally, and by following other contributions, such as those of [5,19,30], we opted for including other potentially relevant variables in the empirical model, to accurately capture the influence of each determinant. Thus, control variables such as marital status, parenthood, and public subsector were also considered.

Figure 1. Conceptual model.

3. Materials and Methods

3.1. Questionnaire

Data collection relied on primary data, obtained through an online questionnaire. Such method for data collection is particularly suited when information to be gathered is compatible with the rather standardized and closed questions and when there is a wide geographical area to be covered. This was the case of this study, which aimed to collect information and perceptions of the nation-wide public sector workers on their professional training and considered the inexistence of secondary data with the variables needed to test our hypotheses. Other advantages attributed to online questionnaires include their ease and low cost to be administered, fast delivery and the fact that respondents may answer when and where they wish, at their convenience, within the deadline indicated [39].

Given the novelty of this specific topic—digital training in the public sector—we could not identity a previously implemented questionnaire with a similar object of interest that could be adopted or adapted for this study. Thus, all questions were developed from scratch, but they were based on the relevant literature and experts' opinions, keeping in mind the variables needed to test our hypotheses.

The questionnaire included four sections, following an introduction that aimed to clarify the scientific objectives of the survey, provide the necessary information regarding anonymity assurance and obtain the respondents' consent to use the obtained data exclusively for academic purposes, as well as apply a macro-level analysis. In the first section, information about the training incidence and training benefits was asked, considering the previous two years. The incidence of training was distinguished between training in general and in the digital fields; between organization- and worker-initiative and between on-the-job and off-the-job training. A perception of the importance of training sessions for 12 potential financial and non-financial benefits was also inquired, considering a 1–5 Likert scale (with 1 corresponding to "no contribution" and 5 to "high contribution"). The potential benefits considered were: Wage increase; career progression; technique actualization; improvement in general competences; productivity/performance improvement; adaptation to new tasks; improvement in legal domains; improvement in software manipulation; better relationship with citizens; improvement in foreign languages; better relationship with peers; better relationship with chiefs (a Cronbach's alpha of 0.86 was obtained, revealing a good

internal consistence). Then, a variable (perceived training benefits) was determined from the average of the level of importance attributed to each training benefit, corresponding to a proxy of the value each worker perceives from professional training.

In the second section, each worker was asked to classified their knowledge in 12 digital competences, using a 1–5 Likert scale between "non-qualified" and "highly qualified". These digital competencies were defined by combining information obtained from the DigComp framework, from existing training programs for public administration in digital tools and through experts' consultation (particularly, with the contribution of three higher education professors, who also collaborate with the public sector in specific digital training programs). The list of the 12 digital competencies includes: Word; Excel; software for presentations; internet and email; communication systems; dataset management; big data management; cybersecurity; social media; cloud technology; web page construction; video/images edition (with excellent internal consistence, considering a Cronbach's alpha of 0.92).

In the third part, the respondents were asked to identify their training needs in the digital fields by classifying the importance (from 1—"nothing important" to 5—"extremely important" in a Likert scale) of having training in the 12 digital competences used in the previous section (Cronbach's alpha of 0.90).

In the last section, demographic and professional information was requested, namely: gender, age, schooling, marital status, parenthood, residence county, occupation, job tenure, type of professional contract and public subsector.

After being submitted to a pre-test by human resources' specialists working in distinct subsectors of public services and having made the necessary adjustments, the questionnaire was sent by e-mail for several public organizations in the whole country: Local government entities, employment offices, social security offices, schools, courts, fiscal offices and public hospitals. It was also posted on social media. The answers were collected for a month, between 11 November and 16 December 2020. Complete information was obtained for 573 workers.

The participants' answers were extracted from the Google Forms platform through an Excel file. After this procedure, the data were exported to Stata software in order to estimate the models and other relevant statistics.

3.2. Sample Summary Statistics

In Table 1, some summary statistics are presented, considering the sample distributed between three groups of workers:

Table 1. Summary statistics—Mean and Standard Deviation (SD).

Variable	Description	No-Training Mean (SD) (1)	Training in Non-Digital Field Mean (SD) (2)	Training in Digital Field Mean (SD) (3)
Gender (Female)	Dummy: 1 if the worker is female; 0 otherwise.	62.9%	72.3%	69.4%
Age	Continuous variable tracking worker's age.	45.3 (9.45)	45.9 (8.54)	46.8 (8.10)
Schooling	Number of years of schooling.	15.0 (3.02)	15.3 (2.41)	15.9 (2.52)
Marital Status (Married)	Dummy: 1 if the worker is married; 0 otherwise.	62.9%	65.2%	69.4%

Table 1. *Cont.*

Variable	Description	No-Training Mean (SD) (1)	Training in Non-Digital Field Mean (SD) (2)	Training in Digital Field Mean (SD) (3)
Parenthood	Dummy: 1 if the worker has children; 0 otherwise.	72.7%	77.0%	73.8%
Professional qualification	Qualification level, ranked between 1 to 6, with 1 being the lower qualification (operational assistants) and 6 the highest (local government representatives).	2.8 (1.37)	3.0 (1.50)	3.3 (1.39)
Seniority	Number of years the worker is employed in their current organization.	15.1 (10.52)	16.2 (11.05)	17.2 (11.30)
Temporary contract	Dummy: 1 if the worker has a temporary professional contract; 0 otherwise.	15.2%	10.6%	12.5%
Public subsector				
Local administration	=1 if the worker is employed in the respective public subsector (Local administration, Education, Health, Justice, Finances, Social security and other subsectors), 0 otherwise.	62.9%	54.3%	36.2%
Education		20.5%	19.5%	24.4%
Health		3.8%	4.6%	2.5%
Justice		1.5%	4.9%	2.5%
Finances		6.8%	13.5%	28.8%
Social security		1.5%	1.4%	4.4%
Other subsectors		3.0%	1.8%	1.2%
Training sessions	Number of training sessions in the last two years.	---	3.8 (5.25) [1]	5.4 (3.72)
Self-initiativeparticipation	Percentage of sessions where the worker had participated by self-initiative.	---	67.3%	62.8%
On-the-job training	Percentage of sessions that occurred during the labor schedule.	---	73.4%	75.1%
Perceived training benefits	Average of the level of importance attributed to each training benefit.	---	2.3 (0.81)	2.8 (0.85)
Number of observations		**132**	**281**	160

[1] The high value of the standard deviation is due to an outlier, which, however, does not affect the model's results.

(a) No-training group (including all the individuals that referred to not having participated in training over the last two years) with 132 workers—Column 1;

(b) Non-digital training group (those that had participated in training sessions, but not in the digital fields) with 281 workers—Column 2;

(c) Digital training group (those that had participated in training sessions in the digital fields) with 160 workers—Column 3.

Although we did not apply a probability sampling technique, preventing from making statistical inferences about the population's characteristics, our sample statistics are very similar to the statistics of the population of Portuguese public service workers, considering its composition according to gender, age and job contracts. Regarding the education level, our sample composition reveals a higher weight of highly educated people, when compared to the generic profile of public sector workers. In order to evaluate results' sensitiveness to this mismatch, we compared the results obtained by estimating the model for different subsamples.

Among the 573 workers in our sample, 72% (=(132 + 281)/573) had not participated in training sessions in the digital fields over the last two years. The majority of workers are female and this proportion is especially high in the second group—workers with training

in other fields than digital. The average age is around 46 years old and slightly higher for those who participated in training. Education is measured by years of schooling, and the average is closer to the number of years that corresponds to an undergraduate degree. Moreover, schooling years are higher in case of the last group of workers, suggesting that workers with higher levels of schooling participate more in training in the digital fields. Workers in this third group are more often married and have higher job tenure.

Professional qualification is a variable with values between 1 to 6, and was constructed by considering worker occupation (for example, the value 1 was attributed to operational assistants, 2 to technical assistants and 6 to local government representatives). This variable is related with skills acquired at work, and since its average is higher in column (3), this might suggest a positive relation between digital training and job-specific skills. Permanent contracts are predominant among workers in the sample (88% in the whole sample) with the percentage of temporary workers being higher in the group of non-trained workers (15.2% against 10.6% and 12.5% in columns (2) and (3)).

The distribution of workers between public subsectors is also very different between columns (1), (2) and (3), which might be associated with greater/lesser willingness to participate in training from workers/organizations in different subsectors. Clearly, local administration has a high weight in the sample, but this percentage is lower between workers who participated in training in the last two years and even lower when only training in the digital field is considered. On the other hand, workers in the finance subsector correspond to 28.8% of total workers that had trained in digital fields, a much higher percentage than its weight in the total sample, which also occurs with workers in the education subsector.

For workers that had participated in non-digital training, the average is 3.8 participations in the last two years, while for those that participated in training in digital tools, the average is higher and corresponds to 5.4. The on-the-job training has a higher percentage between the group of workers that had digital training, and the self-initiative participation is higher in non-digital training, suggesting that public organizations recognize the importance and promote training in digital fields more often. Finally, workers that had participated in training in digital fields recognize more benefits from training than those in general (non-digital) fields.

3.3. Model

In accordance with the literature (e.g., [5]), we used a linear probability model to estimate a binary variable T_i that will be =1 if worker i participated in training sessions over the last two years and =0 otherwise:

$$T_i = \alpha_0 + \beta X_i + \theta Z_i + \varepsilon_i \quad (1)$$

X_i corresponds to a set of personal characteristics of worker i, such as gender (=1 if female, =0 if male), age (in years), schooling (in years), marital status (=1 if married, =0 otherwise) and parenthood (=1 if the individual has children, =0 if not). Z_i is a vector that identifies professional characteristics of worker i such as professional qualification (a variable with values between 1 and 6, where 1 corresponds to the lowest qualification); job tenure (in years); and public subsector (education, health, justice, finance, social security, other subsectors and local administration, which is the baseline category). α_0, β and θ are the parameters to be estimated and ε_i denotes the error term.

Then, a similar model is used to investigate how personal and professional characteristics influence the probability of participating in training in the particular case of digital fields (DT_i): (In Equation (2), the parameters to be estimated are α_1, γ and δ, with μ_i being the error term)

$$DT_i = \alpha_1 + \gamma X_i + \delta Z_i + \mu_i. \quad (2)$$

4. Results

4.1. Competences and Training Needs in Digital Fields

In Figure 2, the competences in the digital fields perceived by workers as well as their training needs are presented for the whole sample and for the three groups of workers. Considering the complete sample (Figure 2a), on average the respondents classified their digital literacy between the basic and the intermediate level (average = 2.70 on a 1–5 scale). Word, (3.59), Internet and email (3.58) and Excel (3.12) are the competences with the highest average values of perceived knowledge. On the contrary, workers are considered to have lower knowledge in the construction/management of web pages (1.73), big data management (1.98) and image/video editing (2.00).

When the sample is separated by groups—Figure 2b–d, the same competences are evidenced as those with the highest and lowest level of perceived knowledge (and in the case of the "no-training" group, cybersecurity is also included in the list of the lower competences). However, comparing the three groups of workers, we found that the average level of perceived knowledge of the digital training group is significantly higher than the average level of the other two groups. By consequence, the competence levels presented by the digital training group are always above the average levels of the complete sample, with higher differences for the cybersecurity (2.56 vs. 2.12), web page construction (2.08 vs. 1.73) and dataset management (2.8 vs. 2.51) skills. Interestingly, the two subsamples with no training on the digital fields present very similar average levels for the digital competences.

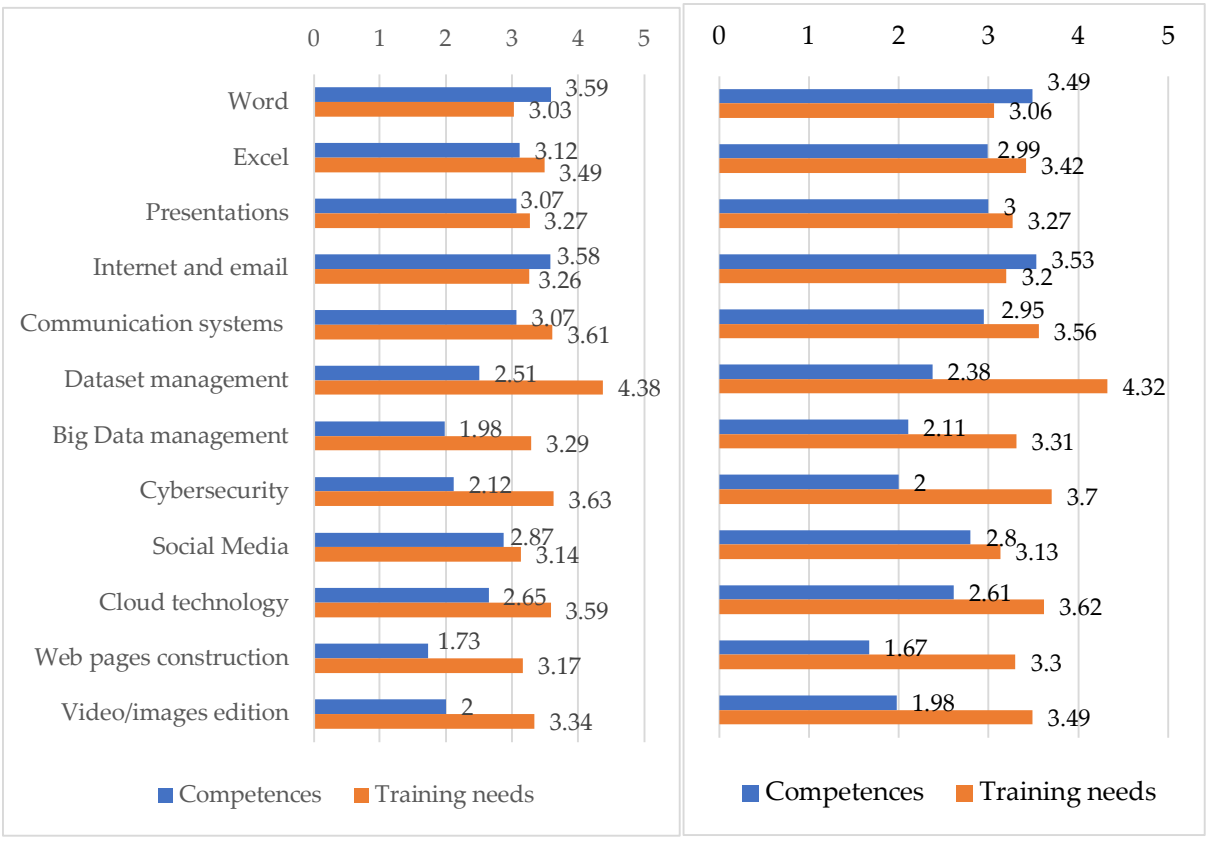

Figure 2. *Cont.*

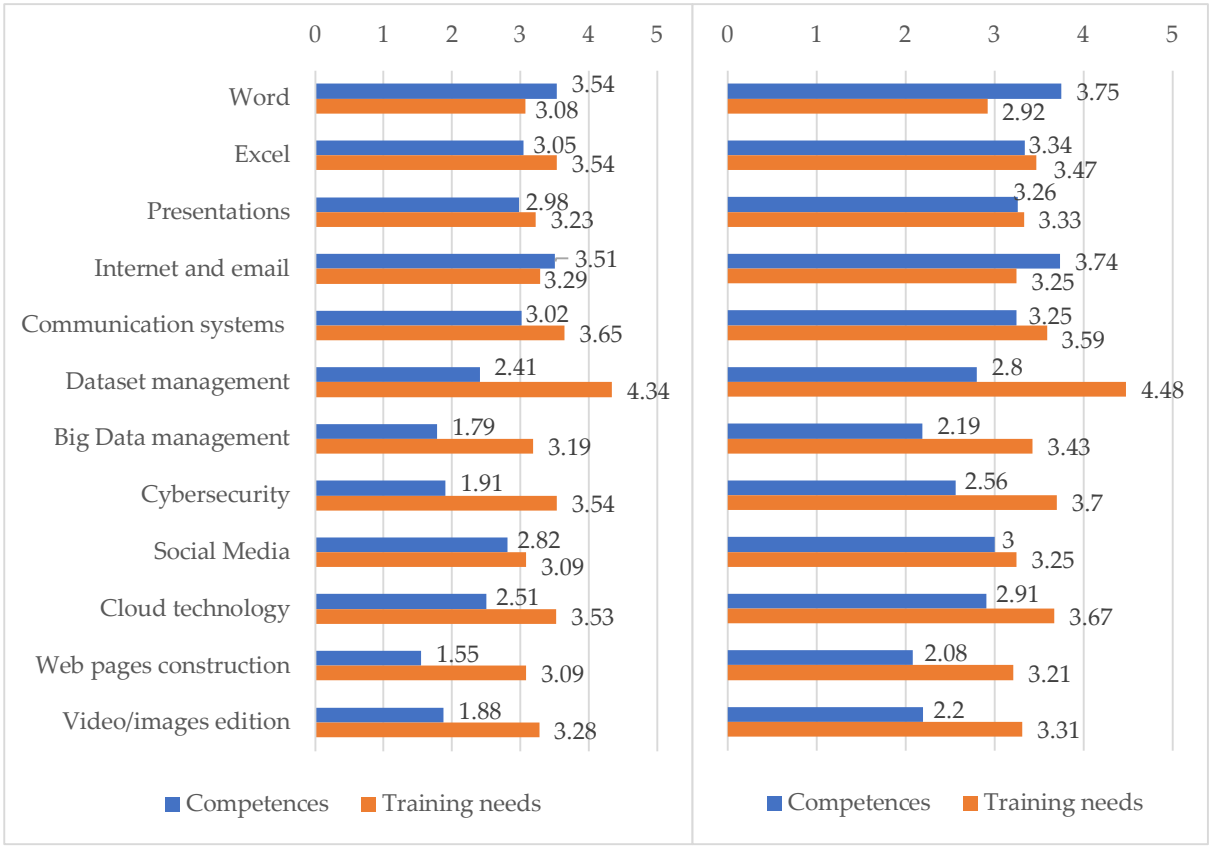

Figure 2. Digital competences and training needs perceived by workers. (**a**) Complete sample. (**b**) No-training group. (**c**) Training in Non-digital field group. (**d**) Training in Digital field group.

In relation to training needs, and again considering the whole sample (Figure 2a), the higher average value is obtained in the case of dataset management (4.38)—this clearly indicates the importance that workers give to this competence, since it is not on the list of the lowest knowledge. For those that had already participated in training in digital fields, while recognizing a higher knowledge in dataset management than the remaining workers, this competence is even more valued—the average of the importance of training in this skill is 4.48. Although not presented in Figure 2, a further analysis of our dataset allowed us to conclude that this training need is especially high in the subsectors of health and social security.

Moreover, by comparing the previous knowledge with training needs, it seems that training in communication systems and training in cybersecurity are both valued; however, while the first is a mean to reinforce the knowledge already attained, the second is considered to be very important (particularly, in the subsectors of justice and health) to overcome the weak knowledge revealed by the workers. In contrast, the web page construction and video/images editing are not very important from the perspective of workers in the public sector since, even though they recognize low knowledge, they do not spot high training needs in this field. Finally, training needs are low in the case of Word and social media, which could be explained by the higher values presented for the perceived knowledge in these fields.

Interestingly, the group that provides more importance to future training in the digital field is the digital training group (that had already acquired some skills in this field), which might be due to these workers being able to recognize more benefits to training (this will be investigated in the next subsection). This comparison between the digital training group with the other two groups and the complete sample also allowed us to conclude

that training needs of this group are relatively higher for the competences in big data management and social media (and the abovementioned dataset management) and lower in the case of Word competences.

Finally, is also interesting to notice that the group that had not participated in training in the last two years reveals a higher interest in participating in training sessions in the digital fields than the group that have been participating in training but not in the digital fields. The comparison of the perceived competences with the training needs of these two groups of workers suggests that training in a non-digital field and training in a digital field might not have a complementary relationship (especially when the more advanced digital competences are considered).

4.2. Perceived Benefits of Training

In Figure 3, we present the average of the perceived contributions of training to the various potential benefits for the "non-digital training" group and the "digital training" group.

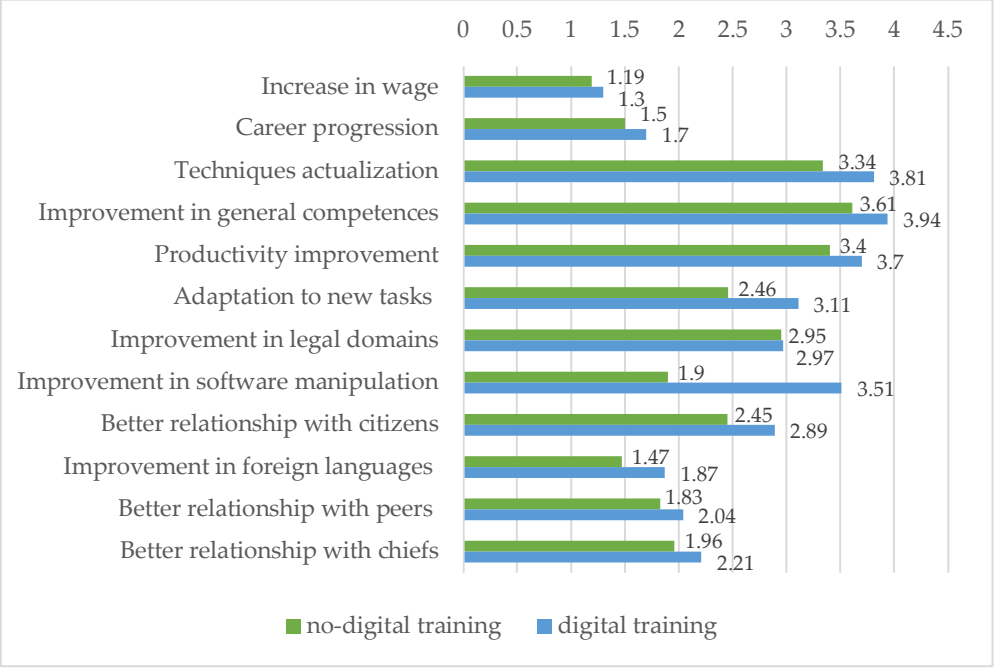

Figure 3. Perceived benefits of training.

The professional training contributes mainly to the improvement of skills in general, the updating of techniques and to the improvement of the worker's performance/productivity. In turn, the workers in the sample express that the participation in training has little or no contribution to wages' increases and career progression, as well as to improving communication in foreign languages.

Comparing the two groups of workers, we conclude that the digital training group perceives a higher value from all the potential benefits of training than the other group (for each category, the averages of the perceived benefits are always higher in the case of the group that had participated in the training in the digital field than in the case of the group that had training in non-digital fields). These results might be explained by the fact that digital competencies are more directed towards 21st century skills, which are highly determined by automation and digitalization, and thus are acknowledged by public servants as essential for them to be prepared for the increasing challenges in public services, which leads to a greater recognition of its benefits. As expected, considering the type of training received, differences are particularly higher in the case of the improvement in software manipulation, but also higher in the case of the adaptation to new tasks, technique

actualization and the contribution to improve the relationship with citizens. Although not observable in Figure 3, we also note that workers who take the initiative to participate in training are those who mostly value the contributions of professional training.

4.3. Models' Estimation—Propensity to Participate in Professional Training

In Table 2, we present the results obtained by estimating Equation (1)—Column (1) and Equation (2)—Column (2). The log-likelihood ratio with a *p*-value < 0.001 indicates that some demographic and professional variables of workers influence their propensity to participate in professional training, and the Variance Inflation Factor (VIF) tests (average of 1.35 and a maximum value of 2.29) point to the inexistence of multicollinearity problems.

Table 2. Probit Model.

Variable	Non-Digital Training Incidence (1)	Digital Training Incidence (2)
Constant	−0.5801	−1.9839 ***
Gender (Female)	0.2623 **	0.0588
Age	0.0001	−0.0004
Schooling	0.0497 *	0.0510 *
Marital Status (Married)	0.0872	0.1529
Parenthood	0.0346	−0.1355
Professional qualification	0.0489	0.1012 **
Job tenure	0.0014	0.0021
Temporary contract	−0.2433	−0.0450
Public subsector		
Education	0.0764	0.1838
Health	0.1567	−0.1111
Justice	0.6145	−0.1402
Finances	0.6986 ***	0.8006 ***
Social security	0.4268	0.9501 ***
Other sectors	−0.3127	−0.1736
Number of observations	573	573
Log-likelihood ratio	32.60 (0.0033)	51.92 (0.0000)

* *p*-value < 0.1, ** *p*-value < 0.05, *** *p*-value < 0.01.

In relation to schooling, the results are in line with previous authors, who argue that workers with higher levels of education are those who are more involved in training, pointing to schooling and training as complementary [11–13,30,31]. Thus, Hypothesis (1a) is verified for both types of training—in digital and non-digital fields. On the other hand, professional qualification seems to be determinant for the incidence of digital training, but not significant for non-digital training, which partially confirms Hypothesis (1b). Therefore, complementarity between training and job-specific skills is more important in the case of the digital field.

Neither age and job tenure are significant determinants of training incidence. In the case of job tenure, a deeper analysis allowed to observe that workers with a higher tenure in organizations take the initiative to participate in training more often than recent workers (which may demonstrate the willingness to be up-to-date), while organizations tend to offer training especially to apprentices and other newcomers in order to prepare them for their occupations. These two effects balanced each other and may justify the non-significance of the coefficient of tenure in the probability of training. Thus, Hypothesis (2a) is not validated, but Hypothesis (2b) is partially confirmed, as organizations are more prone to offering training to recent workers.

Moreover, according to Table 2, we observe a higher propensity to participate in professional training in the case of female workers but only in the non-digital field, which partially confirms Hypothesis (3). This is in line with the investigation in [38] that justifies

this result by claiming that women have a more positive attitude towards training than men, and with the findings of [15,16].

Generally, the literature indicates that workers with more precarious employment contracts participate less in training, since organizations are less willing to invest in workers with a weak bond with the institution [11]. However, the non-significant coefficient obtained to the temporary contracts may be explained by considering the particularities of the public sector, namely the fact that training is, in the Portuguese public administration system, a condition to obtain a permanent contract. In fact, if we estimate an alternative model where the intensity of training (number of sessions) is used as an dependent variable instead of the incidence (and considering the same set of explanatory variables), we obtain a positive coefficient for workers with temporary contracts, which contradicts Hypothesis (4).

In Table 3, the abovementioned results and their relationship with the hypotheses' validation are summarized, including an indication of the literature that corroborates our results.

Table 3. Summary of hypotheses validation.

Hypothesis	Validation	Similar Results Found in:
H1a: *Professional training incidence is positively related with workers' education level.*	√	[12,13,30–32]
H1b: *Professional training incidence is positively related with workers' professional qualification*	√ for training in digital field	[5,16,30]
H2a: *Professional training incidence is negatively related with workers' age*	X	[5,13,31,35]
H2b: *Professional training incidence is negatively related with job tenure of the worker.*	√ for the organization-provided training	[32,35]
H3: *Professional training incidence is determined by gender, being higher in female workers than in men.*	√ for training in non-digital field	[15,16,37,38]
H4: *Professional training incidence is positively influenced by labor contract stability of workers.*	X	

Considering the statistically significant and positive coefficients of the finance subsector in columns (1) and (2) of Table 2, we conclude that individuals in the sample who work in this subsector are more likely to attend professional training, both in the digital and non-digital fields. If we take into consideration the information on the self/organization-initiative to participate, we observe that this higher propensity to train is particularly evident in organization-initiative training. In other words, organizations from the finance subsector offer training to their workers more often than other public subsectors. Social security workers are also more likely to participate in digital training than the workers from the remaining subsectors.

Finally, Equation (2) was also estimated by including the variable of the perceived training benefits in order to understand whether workers who recognize higher training benefits have a higher probability of participating in digital training (among workers who participate in training). A positive and statistically significant coefficient for this variable was obtained, confirming the importance of motivation in the training incidence for the particular case of the digital field.

5. Discussion and Conclusions

The focus of this study relied on training incidence and training benefits, particularly addressing digital training in the specific context of the public sector. A total of 72% of the public sector workers that answered our questionnaire had not participated in training in the digital field in the last two years. This is a worrying observation, especially when combined with their own perception of a low level of knowledge in digital domains (between the basic and the intermediate level), which forces the adoption of rudimentary

procedures in the execution of certain functions, leading to a lack of effectiveness and efficiency in work performance.

Therefore, the promotion of training programs on a regular basis by organizations and the incentive to participate in training sessions in the digital field (using mechanisms to reward workers for their participation) is essential to enhance the digital competences of public sector workers, and better prepare them for the digital transformation process that is already ongoing. Workers' participation might also be triggered by the dissemination of training benefits, as workers' perception of these benefits seems to be an important motivator for participating in training in digital tools.

Nevertheless, the results of our study are encouraging, since the majority (87%) of respondents reveal a willingness to participate in training in the digital field in the future and recognize significant training needs in this field. Particularly, the workers in the sample demonstrate a significant interest in participating in training in dataset management and communication systems, to reinforce prior knowledge, and in cybersecurity, to fill the knowledge gap in this dimension.

On the relationship between acquired skills and training needs, we observe a negative correlation for the most basic competences (less knowledge; greater need for training), and a positive correlation for the more advanced digital domains (such as database management, big data management and website construction), suggesting that, in this case, those who know more are more interested in reinforcing their knowledge. This last result is in accordance with the findings of [25], which validated a positive correlation between the self-assessed level of competencies and the perceived need and willingness to participate in further training.

This investigation also sought to study the relationship between demographic and professional characteristics and the propensity for professional training through a probabilistic regression model. One of the main results obtained, both for training in digital and non-digital skills, is the evidence that training does not act as a substitute for formal education, but rather as a complement to the knowledge obtained through schooling. In fact, highly qualified and educated workers (and with higher levels of digital skills) had participated more in training and demonstrated a greater interest in participating in training in the future, especially in more advanced domains. This raises an important issue concerning employees with lower human capital levels (lower schooling and/or lower qualification levels): their reduced participation in training may result in widening the skills gap, with inherent risks for the organization and the workers themselves. Possible interventions to contradict such risks include, on the one hand, putting in place motivating incentives to participate (such as public recognition, financial rewards or consideration for career progression) and, on the other hand, designing appropriate training strategies with a sequential approach to contents' demand, so that workers with lower educational levels are able to follow and benefit from training.

The results revealed that female workers tend to attend more training sessions in non-digital training than men, but not in the digital fields. A positive relationship was obtained between job tenure and participation in training sessions by the worker's initiative, which might countervail the higher propensity of organizations to provide training to newer workers. Subsectors are also important determinants of the incidence of training, with finance and social security workers having a higher propensity to participate in training in the digital fields.

Our investigation extends the human capital theory to the specific field of digital knowledge and provides information on the training of workers in the public sector, which is essential for public organizations to better prepare for digital transformation. Information concerning the groups that participate more in training may support policymakers to focus their efforts towards less participating groups. Given the methodology used—survey by questionnaire—it was possible to obtain a significant amount of information and consider the opinion of a large number of participants. Although a non-probability sampling technique was adopted, preventing us to make statistical inferences about the

population's characteristics, our sample statistics are very similar to statistics of the population of Portuguese public service workers, considering gender, age and job contracts. Non neglectable differences were observed concerning the education level, but when models are tested considering different subsamples to overcome this limitation, we obtain robust results, suggesting that they are not very sensitive to this mismatch. However, a possible enlargement of the database, as well as the extension of the study to the private sector (where the process of digital transformation is also of increasing importance), allowing comparisons between the private and public sectors, are suggestions for future investigations. Another interesting path of research to be explored in the future consists in complementing the quantitative approach adopted in this study with qualitative methods (for example, through the use of focus groups with a limited number of participants) that might allow for a better understanding of the reasons and motivations behind the results obtained.

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