Factors Influencing Professional Adoption of Artificial Intelligence

Francisco Malhado

University of Évora

Abstract

This study examines the factors associated with **AI adoption in day-to-day professional activities** through a binary logistic regression model estimated on a national Portuguese survey. The dependent variable is a dichotomous indicator of whether the respondent uses AI at work. Explanatory variables include gender, age, education, region, sector of activity, coding-related tasks, self-assessed AI knowledge, perceived ease of AI in daily life, and attitudes toward risk and benefit. Model diagnostics confirm the adequacy of the specification, with perceptual variables demonstrating the strongest predictive capacity. Higher perceived knowledge and agreement that AI simplifies daily tasks significantly increase the odds of adoption. In contrast, socio-demographic variables and regional differences show weak or null effects. The results indicate that AI usage at work is driven primarily by **subjective perceptions and familiarity**, offering evidence-based guidance for skills development and organizational strategies aimed at strengthening AI readiness.

Keywords: Artificial Intelligence (AI), Logistic Regression, AI Literacy, Perception of AI

Author Note

This research was conducted in collaboration with the DSPA – Data Science Portuguese Association, within the framework of a national study on the perception and adoption of Artificial Intelligence in Portugal. The project was carried out under the scientific supervision of Professor Paulo Infante.

1. Introduction

Artificial Intelligence (AI) is rapidly transforming multiple sectors of society, from finance and healthcare to education and public administration. However, its adoption depends not only on technological availability but also on how individuals perceive its benefits, risks and impact on everyday life. These perceptions are closely tied to the level of trust placed in AI systems, which, as noted by Araujo et al. (2020), is strongly influenced by perceived fairness, transparency and legitimacy of automated processes. Understanding how different groups within Portuguese society position themselves in relation to AI is therefore crucial for informing public policy, shaping communication strategies and promoting an ethical and effective integration of AI technologies.

The aim of the present study is to examine the determinants of **AI usage in daily professional activities** within the Portuguese context. To achieve this, a structured and conditional survey was designed and administered, covering several key dimensions: perceptions of AI in academia and the labor market, self-reported familiarity and knowledge, perceived risks and benefits, trust and transparency, and concrete patterns of AI adoption in professional settings. While the questionnaire included broader attitude and contextual dimensions, the focus of this paper is specifically on modelling the factors that explain whether an employed respondent uses AI tools as part of their everyday work. The remaining attitudinal components of the dataset, which are not examined in the present analysis, will be explored separately through a cluster analysis aimed at identifying distinct perception and adoption profiles within the Portuguese population.

To address this objective, we estimate a **binary logistic regression model**, taking as the dependent variable a dichotomous indicator of AI use in daily professional activities. The model incorporates socio-demographic characteristics, professional context (including whether respondents work with code or data), and attitudinal variables such as self-assessed knowledge, perceived ease of use, and evaluations of AI's risks and benefits. This approach enables a quantitative assessment of how structural and perceptual factors jointly shape the likelihood of workplace adoption.

By isolating the contribution of each predictor while controlling others, the logistic regression model provides a rigorous framework for understanding which attributes most strongly influence the use of AI at work. This analytical focus allows the study to move beyond descriptive perceptions and offer evidence-based insights into the behavioral drivers of AI adoption among Portuguese professionals.

This project was conducted in partnership with the **DSPA – Data Science Portuguese Association**, ensuring alignment between academic research and practical relevance for Portuguese society.

2. Institutional Context

The **DSPA – Data Science Portuguese Association** is a Portuguese non-profit organization recognized as the leading national community dedicated to the promotion, development and dissemination of data science. Its mission is to contribute to a more informed, innovative and technologically capable society, particularly in the use of emerging technologies such as Artificial Intelligence, always guided by principles of ethical responsibility and transparency.

DSPA positions itself as a bridge between academia, the private sector, public administration and civil society, fostering value creation through data-driven knowledge. In this context, it promotes the representation of the data science sector, the sharing of experiences, case studies and success stories, as well as cooperation with public entities, companies and higher education institutions. It also supports entrepreneurship and innovation within Portuguese organizations. In addition, the DSPA provides support for public-interest projects and actively promotes regulation, ethics and security in the use of data science, both in Portugal and internationally.

As part of the present project, the DSPA collaborated with the author with the objective of deepening the understanding of familiarity, perception and adoption of AI across different segments of the Portuguese population. This collaboration not only reinforced the organization's mission to democratize access to data science knowledge but also provided a concrete opportunity to align academic research with the practical needs of society.

The present report is therefore a direct outcome of this partnership, contributing to the **DSPA**'s strategic objectives in the areas of digital literacy, AI capacity-building and the production of empirical evidence to support public policy and technological adoption strategies.

3. Data

3.1. Construction and Administration of the Questionnaire

The questionnaire used in this study was entirely developed by the author as part of the partnership with DSPA. Its design followed recognized best practices in survey research, ensuring scientific relevance and alignment with the association's objectives. The primary purpose of the instrument was to capture multiple dimensions of the perception and adoption of Artificial Intelligence (AI) within Portuguese society.

1. **Academic Context**
   This section examined the use and perception of AI in education and research, both among students and teaching staff. It included questions on the use of AI tools for studying, producing academic assignments, preparing classes and developing scientific projects.

2. **Professional Context**
   It focused on the use of AI in the direct performance of professional duties. The aim was to identify how respondents employ AI in their day-to-day work, for purposes such as task automation, decision support, data analysis, and other job-related activities. This context covered all sectors of activity.

3. **Labor Market Context**

   This section assessed perceptions regarding the structural impact of AI on the labor market, including questions about job displacement, changes in required skills and the need for reskilling. It also included specific questions targeted at respondents with technical profiles.

4. **AI Adoption in Society**

   This section analyzed individual patterns of AI adoption, including the frequency and variety of tools used, concrete situations in which AI is employed in daily life, the use of paid AI services, and respondents' self-assessed level of knowledge about the technology.

5. **Perception of AI-Related Risks**

   This section included a set of items designed to capture the most salient concerns associated with the development of AI. Among the risks assessed were loss of privacy, algorithmic bias, technological dependence, malicious use of AI, job displacement, and the need for regulation and transparency. The section also addressed the role of the State and respondents' trust in institutions responsible for overseeing AI systems.

It is important to note that the questionnaire was conditional, with navigation across sections adapted to each respondent's profile through flow logic implemented on the digital platform. For example, only individuals who identified as students or teaching staff accessed the section dedicated to the academic context, while those who reported working with code were routed to specific questions on AI use in programming environments. This design enabled a deeper exploration of relevant areas without burdening all participants with questions that were not applicable to their circumstances.

Complementarily, the survey included a sociodemographic characterisation section (age, gender, region, educational attainment and employment status), which served as a basis for subsequent profile analyses.

The questionnaire was implemented in digital format using the Google Forms platform, ensuring ease of access and centralized data collection. Its dissemination took place through multiple channels in order to reach different segments of the Portuguese population. First, it was shared by DSPA on LinkedIn, and that post was subsequently amplified by the author and other members of the association's community. Second, it was distributed at the University of Évora to both students and teaching staff, ensuring the inclusion of academic profiles. In addition, spontaneous sharing within personal networks helped widen the survey's overall reach.

The data collection period ran from 19 April to 17 July 2025, corresponding to approximately three months of active dissemination. The process followed a convenience sampling approach based on voluntary participation, which enabled the inclusion of a diverse set of individuals interested in Artificial Intelligence. However, it is important to acknowledge that this procedure does not guarantee a probabilistic sample representative of the Portuguese population, thus constituting a methodological limitation that should be considered when interpreting the results.

A total of 173 valid responses were collected. For the purposes of the **logistic regression analysis**, the sample was restricted to 99 respondents who reported being professionally active (either as employees or as self-employed workers) so that the model could accurately capture the determinants of AI use in the workplace context.

The analytical sample consists of 99 participants, of whom 48% are female and 51% are male.

Figure 1 presents the age intervals used in the descriptive analysis. The graphical distribution shows that most participants are between 25 and 64 years old, with the 45-54 and 35-44 groups being the most represented.

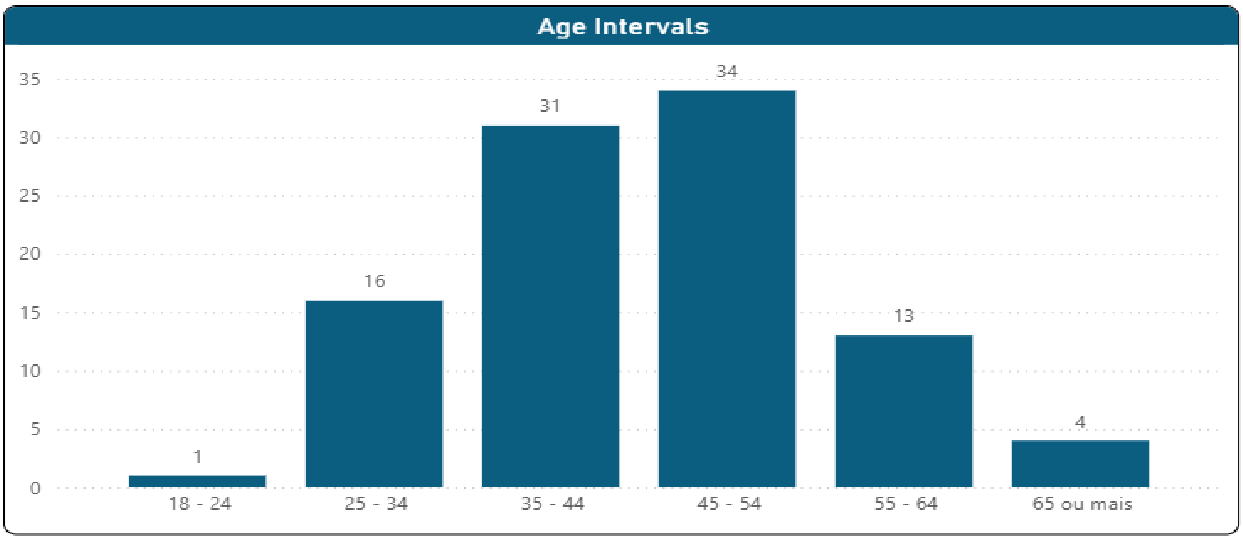

Figure 1 – Age Intervals of the Analytical Sample

Regarding educational attainment, most participants hold a higher education degree. Specifically, 62.63% have a postgraduate qualification, master's degree or PhD, 22.22% hold a Bachelor's degree, and 15.15% completed secondary education.

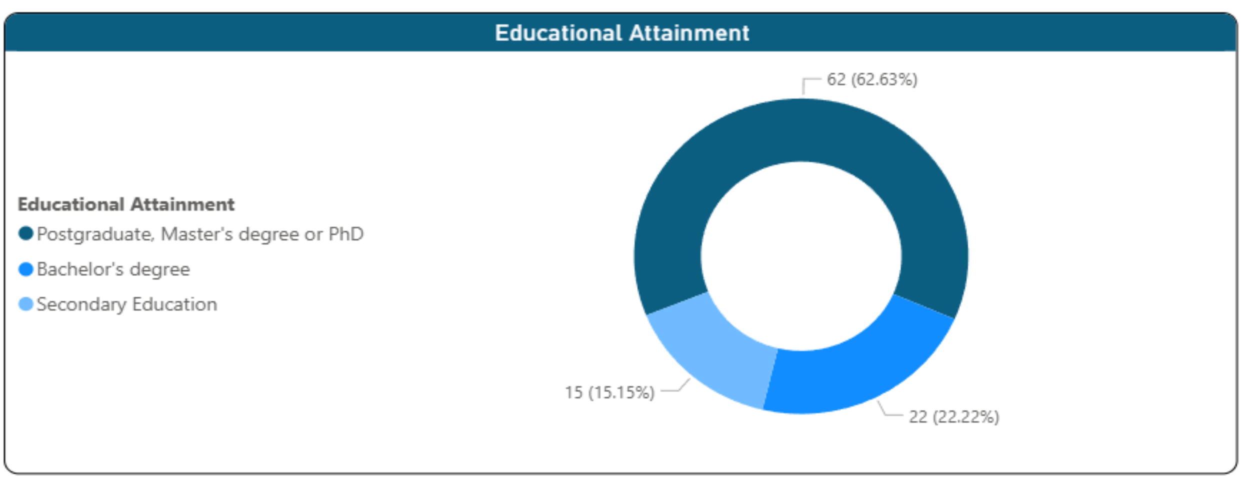

Figure 2 – Distribution of Educational Attainment in the Sample

The regional distribution indicates that most respondents reside in the Lisbon Metropolitan Area (41.41%) or Alentejo (43.43%). Central Portugal accounts for 7.07% of the sample, followed by Northern Portugal (5.05%) and Algarve (2.02%). One respondent reported residing in the Autonomous Regions. This distribution is illustrated in Figure 3.

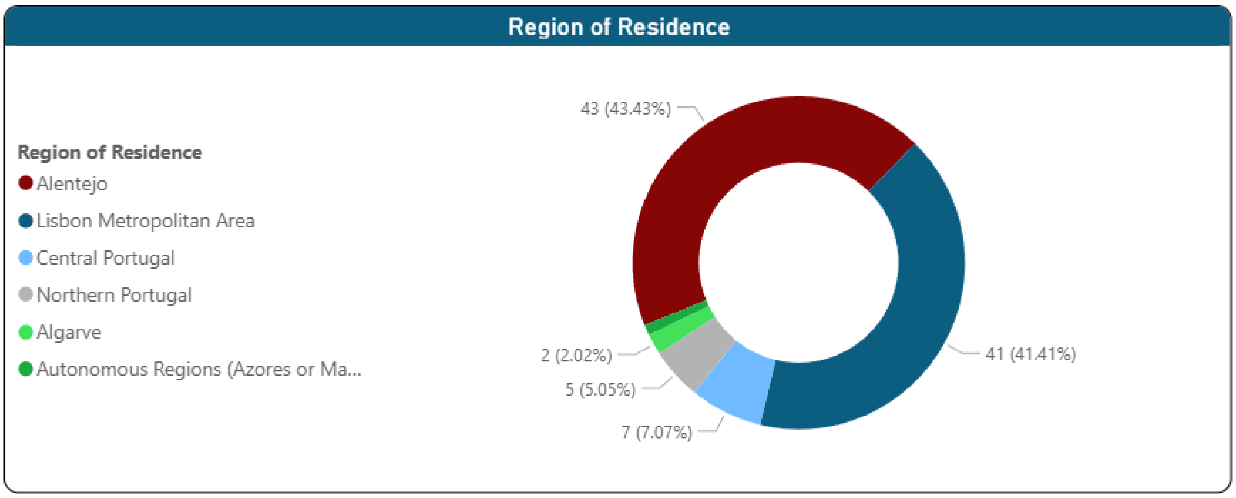

Figure 3 – Regional Distribution

3.2 Data Coding and Pre-processing

After data collection, the dataset was subjected to a systematic process of cleaning, recoding and preparation for analysis. Qualitative responses, such as Likert-type and frequency scales, were transformed into numeric variables while preserving the original ordering and meaning of the categories. All such variables are therefore treated as discrete ordinal indicators.

The dependent variable (T6), which originally recorded whether the respondent uses AI in their day-to-day professional activities ("Yes/No"), was converted into a binary variable, coded as 1 for respondents who reported using AI at work and 0 otherwise. Cases with missing information on this item were removed.

Several explanatory variables were also recoded to obtain analytically meaningful categories and avoid sparse cells. Age (DEM1) was grouped into broader age bands, and region of residence (DEM3) was collapsed into three categories (“Lisbon”, “Alentejo” and “Rest of Portugal”). Educational attainment (DEM4) was simplified by excluding categories with only one observation, and professional sector (T4) was aggregated into broader groups (e.g., “Financial”, “Technology and Business Services”, “Private Services”, “Primary/Industrial”, “Education/Health/Public Services”), ensuring sufficient frequency within each category.

Attitudinal variables were coded as ordered discrete scales. Self-assessed knowledge of AI (AS1) was represented on a 0-4 ordinal scale, with higher values indicating higher perceived knowledge. Agreement with the statement *that “AI has made my life easier in my day-to-day activities”* (AS5) was recoded into three ordered categories (“Disagree”, “Neutral”, “Agree”) and treated as an ordinal factor, with “Disagree” defined as the reference category. Other perception items were encoded in an equivalent way, using 0-2 or 0-4 ordinal coding depending on the number of available response options.

Categorical variables such as gender, region, sector of activity and educational attainment were stored as factors and where required for model estimation, represented through dummy variables with clearly defined reference categories.

Finally, the dependent variable was only administered to respondents who reported being professionally active, either as employees or self-employed. Consequently, the analytical sample for the logistic regression comprises exclusively this group, resulting in 99 valid observations after data cleaning and re-coding.

3.3. Variable Definitions

This subsection describes the variables included in the logistic regression model, distinguishing between the dependent variable and the explanatory variables. All variables were coded and structured according to the procedures detailed in Section 3.2.

Tabela 1 - Variables Used in The Logistic Regression Model

Code	Description	Type (Scale)	Use in Model
T6	Use of AI in daily professional activities.	Binary (0/1)	Dependent Variav
AS1	Self-assed knowledge of AI	Ordinal (0 - 4)	Predictor
AS5	Answer to *“AI has made my life easier in my day-to-day activities”*	Ordinal (0 - 4)	Predictor
MT9	Works with code/programming	Binary (0/1)	Predictor
T4	Professional sector (aggregated categories)	Categorical (5 groups, dummy-coded)	Predictor

4. Metodology

A binary logistic regression analysis was conducted using the subset of respondents who reported being professionally active (either employed or self-employed), with the aim of identifying which sociodemographic and attitudinal factors influence the probability of a professional using AI in their daily work. The methodological approach followed the core principles outlined by Infante (2024), ensuring a coherent structure for defining the dependent variable, selecting predictors and assessing model adequacy. The modelling procedure unfolded through the following steps:

1. **Definition of the analytical subsample and dependent variable:** The regression analysis considered only respondents who reported being professionally active, either as employees or self-employed, with the objective of modelling the factors associated with AI use in a workplace context. Students, unemployed individuals, retirees, and also teachers and researchers were excluded, as they did not access the questionnaire block specifically designed for employed or self-employed workers.

2. **Independent Variables (Predictors):** Based on the literature and the hypotheses under study, several potential explanatory factors were considered for inclusion in the model. These comprised sociodemographic characteristics of the respondent (gender, region of residence and educational attainment), professional context (sector of activity and whether the individual works with code or programming), and attitudes or perceptions toward AI (namely self-assessed knowledge of AI and the degree of agreement with the statement "AI has made my life easier in my day-to-day activities"). The corresponding variable codes for these predictors were: DEM1, DEM2, DEM3, T4, MT9, AS1 and AS5.

3. **Treatment of categorical variables:** Before estimating the model, several categorical variables were regrouped to ensure sufficient representation within each category and to improve the robustness of the estimates. In particular, the various professional sectors were consolidated into five broader categories (e.g., combining similar sectors into groups such as "Primary/Industrial", "Education/Health/Public Services", "Financial", "Technology and Business Services" and "Private Services"). Additionally, the Likert-scale responses for variable AS5 were recoded into three groups ("Agree", "Neutral", "Disagree"), condensing the levels of agreement and disagreement to simplify the analysis and strengthen interpretability.

4. **Model Specification and Estimation:**A multiple logistic regression model (with a logit link function) was then estimated for the dependent variable T6, initially including all previously identified variables as predictors. The model was fitted using maximum likelihood estimation and subsequently simplified based on the statistical significance of the coefficients: non-significant predictors were progressively removed, with nested models compared through likelihood ratio tests (differences in deviance) to assess whether each removal resulted in a loss of model fit. This iterative selection procedure produced a parsimonious final model containing only predictors with statistically significant effects. During calibration, the absence of multicollinearity among the predictors was also verified, as all Variance Inflation Factors (VIF) were well below commonly accepted thresholds.

5. **Model Evaluation:** The quality and adequacy of the logistic model were assessed using several indicators. Nagelkerke's R^2 was computed to quantify the proportion of variation in professional AI use explained by the model. The Hosmer–Lemeshow goodness-of-fit test was used to evaluate model calibration by comparing predicted probabilities with observed outcomes across deciles of risk (Hosmer, Lemeshow & Sturdivant, 2013). The high p-value obtained (0.446) indicates no significant deviation between the model and the empirical data, confirming an appropriate fit. Finally, the model's predictive and discriminative capacity was examined through the Receiver

Operating Characteristic (ROC) curve and its corresponding Area Under the Curve (AUC), which assess the model's ability to correctly distinguish between individuals who use and do not use AI in their professional activities. Together, these criteria validated the proposed model before proceeding to the interpretation of its results (presented in the Results section).

5. Results and Discussion

The purpose of this analysis is to identify the factors that influence the probability of using AI in professional activities. There is evidence of sectoral inequalities in technological adoption, with financial and technology-oriented industries typically integrating AI earlier and more intensively than public sector domains such as education and health. Market studies support this distinction; for example, data from Forrester indicate that generative AI adoption plans in the public sector lag significantly behind those of the private sector (40 - 50% compared with around 90%). This discrepancy suggests that, without targeted public policies and investment, public organizations may face increasing technological disadvantages. Understanding the determinants of professional AI adoption is therefore essential for informing innovative policies, capacity-building strategies and infrastructural support that promote a more equitable digital transition.

To examine the factors that influence the professional use of Artificial Intelligence (AI), a binary logistic regression model was estimated. Figure 4 presents the results in the form of odds ratios (OR), accompanied by their corresponding 95% confidence intervals.

The odds ratio compares the **odds** of an event occurring (in this case, the use of AI in a professional context) with the odds of it not occurring. For example, an OR of 2 indicates that the likelihood of using AI is twice as high as the likelihood of not using it. Values greater than 1 reflect a positive effect (a higher relative likelihood of use compared with the reference group), whereas values below 1 indicate the opposite.

The vertical red line at OR = 1 represents the point of no effect, meaning that the predictor does not alter the relative likelihood of AI use compared with the reference category. Most coefficients lie to the right of this line, indicating a positive association with the likelihood of adopting AI in professional activities. However, statistical significance is determined by whether the confidence intervals exclude 1, not solely by the position of the point estimate.

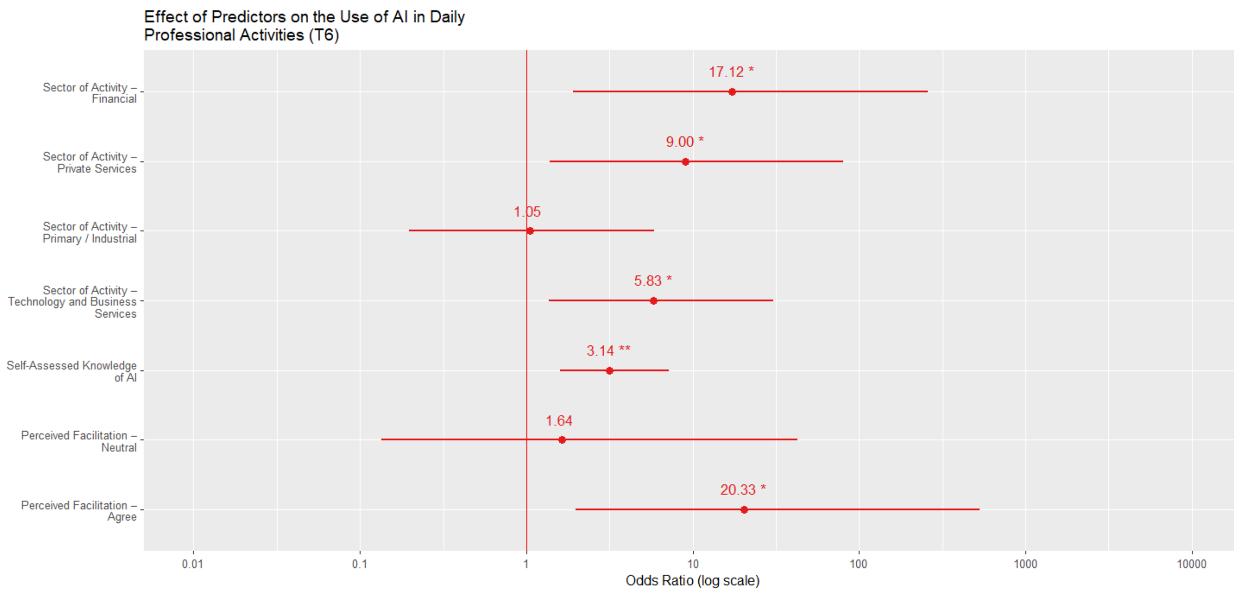

Figure 4 – Estimated Odds Ratios for the Use of AI in Daily Professional Activities (T6).

Table 2 – Estimated coefficients, standard errors, p-values and odds ratios (OR) for each variable in the logistic regression model for "Use of AI in Daily Professional Activities (T6)".

Variable	Reference Category	Category	Coefficient	Standard Error	p-value	Odds Ratio
Sector of Activity (T4)	Education / Health / Public Services	Financial	2.839	1.727	0.000775	17.2
		Private Services	2.198	1.231	0.021063	9.00
		Technology and Business Services	1.763	0.779	0.030975	5.83
		Primary/Industrial	0.046	0.850	0.956621	1.05
Perceived Facilitation (AS5)	Disagree	Agree	3.012	1.339	0.02454	20.33
		Neutral	0.496	1.363	0.71606	1.64

Self-Assessed Knowledge (AS1)	-	Ordinary Scale (treated as continuous)	1.14526	0.379	0.02374	3.14

Although the final model includes some variable categories that do not display statistically significant coefficients, their retention is justified on conceptual grounds and for interpretative consistency. In the case of T4 (sector of activity), even though only some categories show significant effects relative to the reference group, the variable was kept in the model to account for the diversity of professional contexts and to avoid distortions that could arise from its partial exclusion.

In the case of AS5, although the category expressing agreement with the statement shows a statistically significant and interpretable effect, other categories—such as the "Neutral" response—did not reach statistical significance. Even so, the full variable was retained in the model to preserve the ordinal structure of the scale and to maintain interpretative coherence across response levels. While this choice is not fully aligned with the strict principle of parsimony, it is justified by its contribution to a more complete understanding of the different attitudinal profiles associated with AI adoption.

After the sequential analysis of several model specifications and their comparison through likelihood ratio tests, the final logistic regression model includes as significant predictors the professional sector (T4), the self-assessed level of knowledge about AI (AS1), and the degree of agreement with the statement "AI has made my day-to-day life easier" (AS5).

A first notable result concerns the effect of the professional sector. Relative to the reference group (Education, Health and Public Services), individuals working in the Financial sector show an OR = 17.14 (95% CI = [1.909, 258.2]). In practical terms, holding all other factors constant, they have approximately seventeen times higher odds of using AI in their professional activities. Professionals in the Technology and Business Services sector also exhibit a significantly increased likelihood, with an OR = 5.83 (95% CI = [1.35, 30.64]), corresponding to almost six times higher odds of adoption. Those working in Private Services present an OR = 9.00 (95% CI = [1.388, 80.164]). By contrast, individuals in the Primary and Industrial sector display an OR = 1.05, close to the point of no effect and not statistically significant.

Regarding knowledge about AI, a clear progressive effect is observed. For each one-unit increase in self-assessed AI knowledge (AS1), the odds of using AI professionally are more than triple (OR = 3.14, 95% CI = [1.59, 7.18]). This result suggests that digital literacy plays a critical role in the adoption of AI tools in the workplace.

Finally, the degree of agreement with the statement *"AI has made my day-to-day life easier"* (AS5) emerges as the most influential determinant. Individuals who agree with this statement have odds of using AI in their professional activities that are approximately twenty times higher (OR = 20.32, 95% CI = [1.98, 533.52]) than those who disagree. By contrast, respondents who select the neutral option do not exhibit a statistically significant effect. By contrast, individuals who position themselves as neutral do not exhibit a statistically significant effect.

Despite the relevance of the results obtained, it is important to acknowledge that the sample used in this study was constructed through convenience sampling and disseminated exclusively via online channels. Although this strategy was effective in enabling rapid data collection, it introduces a significant limitation in terms of the statistical representativeness of the Portuguese population. Consequently, the findings presented here should be interpreted with caution and cannot be generalized to the national population without reservation. For future research, the implementation of probabilistic sampling strategies is recommended in order to ensure greater inferential robustness and enable more reliable extrapolations regarding patterns of perception and adoption of Artificial Intelligence in Portuguese society.

6. Conclusions

The logistic regression analysis revealed clear statistical evidence regarding the determinants of professional use of Artificial Intelligence within the analyzed sample. Among the significant factors, three stand out: the impact of the professional sector, the respondent's self-assessed level of AI knowledge, and the perceived benefit associated with its use. These results are not only statistically robust but also carry important practical implications.

From a sectoral perspective, professionals in the financial and technology-related industries exhibit a much higher likelihood of using AI compared with their counterparts in the public sector. This result is not merely a statistical finding but reflects structural trends observed in other countries and corroborated by market evidence. The delay in AI adoption within the public sector, highlighted in international studies such as those by Forrester, creates a risk of digital dualization, whereby essential public services fail to keep pace with the ongoing technological transformation.

Moreover, the effect of self-assessed AI knowledge highlights the role of digital literacy as a key enabler of technological adoption. Access to technology alone is not sufficient, individuals must also understand it, both in terms of its technical functioning and its transformative potential. This finding reinforces the need for public policies that promote continuous training and reskilling.

Finally, perceived usefulness, captured by the variable AS5 (agreement with the statement "AI makes my day-to-day life easier") emerges as the most influential factor. This finding points to a subjective yet powerful dimension, the experience of concrete benefit is what most strongly drives adoption. This has important implications for how AI should be promoted among professionals. Beyond technical arguments, it is essential to highlight tangible and impactful applications in everyday professional practice.

In summary, the results of the logistic regression model reinforce the notion that the adoption of AI does not depend solely on the availability of the technology itself, but above all on organizational structures, human capital and the perceived value it generates. Coordinated action across these three dimensions will be essential to ensure an inclusive and effective digital transition.

It is important to reiterate, however, that this study is based on a convenience sample collected exclusively through online channels. This entails a significant limitation for the generalisation of the findings to the Portuguese population as a whole, as statistical representativeness is not guaranteed. Consequently, the conclusions should be interpreted with caution and viewed as indicative of patterns observed within a specific segment of the population. For future research, the use of probabilistic sampling methods is recommended, as these would enable more robust inferences and more reliable extrapolations to the national population.

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