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AI and the Future of Professional Work: Task-Level Drivers of Employees' Perceived Replacement Risk in Professional Service Firms

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Abstract

The thesis addresses a highly topical issue for Professional Service Firms (PSF): the impact of artificial intelligence on the structure of consulting work and the possible equivalence of exposure between junior and senior profiles. The relevance derives from the rapid spread of generative systems in the typical tasks, with implications for productivity, skill mix and team organization. The subject of the investigation is: (i) how the characteristics of the work activities carried out in the Professional Services Firms (PSF), in particular the level of standardization of tasks, the degree of empathy and negotiation skills required, the severity of the consequences deriving from any errors, the requirements of confidentiality and protection of data privacy, the time pressure on deliverables and the level of novelty and ambiguity of activities, influence the perceived risk of replacement of humans by technologies based on artificial intelligence. Six hypotheses are tested, focusing on H1: a higher level of task standardization is positively associated with a greater perceived risk of replacing humans by AI-based technologies. H2: A higher level of empathy and negotiation skills required by tasks is negatively associated with the perceived risk of humans being replaced by AI-based technologies. H3: A greater severity of the consequences deriving from any errors in the performance of tasks is negatively associated with the perceived risk of replacing human work by technologies based on artificial intelligence. H4: Higher requirements for confidentiality and data privacy associated with tasks are negatively associated with the perceived risk of humans being replaced by AI-based technologies. H5: Increased time pressure on deliverables is positively associated with the perceived risk of humans being replaced by AI-based technologies. H6: A higher level of task novelty and ambiguity is negatively associated with the perceived risk of humans being replaced by AI-based technologies. The state-of-the-art shows that AI improves productivity and quality on well-structured tasks, with often greater benefits for the less experienced; In tasks outside typical boundaries, the risk of error and the need for supervision increases. The literature on PSFs also highlights that adoption and impacts depend on governance and organizational readiness. However, important gaps remain: little quantitative evidence outside the audit; few micro analyses for seniority; limited specific task-based measures for consultancy and lack of comparable Italian data. To fill these gaps, the thesis proposes a multi-firm survey. The analysis includes OLS models with interactions and robustness checks. Expected contributions: a credible estimate of the equivalence of exposure between levels, a map by function of the risk and benefit drivers and operational implications on policy, training and team design.

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1. Introduction

The most powerful instrument developed in recent years is Artificial intelligence, innovative instrument able to elaborate data and replicate actions thought only for living beings, so powerful and complex that many people cannot explain yet what it is and how it works.

Today, AI is able to effectively carry out complex programming tasks on real code, advanced academic reasoning and multimodal understanding: on the new tests introduced in 2023, in just twelve months systems have jumped from 4.4% to 71.7% of problems solved on SWE-bench (Software Engineering Benchmark) like bug-fixing on open source repositories, marking a substantial progress in the correction and code generation; at the same time, the score grew by +48.9 % on GPQA (graduate-level questions) and by +18.8 % on MMMU (multimodal reasoning on heterogeneous tasks). In addition to benchmarks, the report notes strong strides in generative video and documents that in some contexts, LLM-based agents outperform human teams in time-limited programming tasks (AI Index Steering Committee, 2025).

It is possible to train reinforcement learning agents without an explicit reward function, learning it instead from human preferences: evaluators observe short pairs of sequences of the agent's behaviour and indicate which one they prefer; from these choices, a supervised reward model is trained, which is then optimized by the agent with deep reinforcement learning. With several comparisons, the method allows effective policies to be learned in simulated robotic tasks, showing that AI can align with human goals even when it is difficult to formally specify a reward. At the same time, the work highlights practical limitations: cost and efficiency of human feedback, risk of bias in the learned reward model, and potential reward hacking if the proxy does not faithfully capture preferences (Christiano et al., 2017).

The BERT system introduces a bidirectional pre-training paradigm for language understanding based on Transformer encoders and two self-supervised objectives: Masked Language Modelling (MLM), which involves masked tokens using left and right context, and Next Sentence Prediction (NSP), which classifies whether a second sentence really follows the first; pre-trained on Books Corpus and Wikipedia and then fine-tuned with minimal architectural upheavals, BERT sets new state-of-the-art on three key Natural Language Understanding (NLU) benchmarks: General Language Understanding Evaluation (GLUE), a suite of heterogeneous tests that measures general language comprehension; “SQuAD”, a question answering dataset on Wikipedia in which the model must extract the correct answer from the text; and Situations With Adversarial Generations (SWAG), a common sense inference test in which, given a brief context, the most plausible continuation must be chosen from four options (Devlin, et al., 2018).

Contemporary AI is driven by foundation models: systems trained on large and general data (e.g., BERT, DALL· E, GPT-3) and then adapted to a wide range of downstream tasks, which enables cross-cutting applications in language, vision, robotics, reasoning, and human interaction, as well as in areas such as law, healthcare, and education. These models introduce a real paradigm shift, because the scale of training leads to emergent capabilities and high cross-task reusability; however, their very centrality creates a homogenization effect: the defects of the "basic" model can propagate to all derivative applications. The report also points out that, despite imminent deployment, we still imperfectly understand how and when these systems fail, indicating the need for interdisciplinary research and governance that is attentive to social risks (Bommasani, et al., 2021).

To train large language models efficiently, it is necessary to balance the size of the model on the selected parameters and the amount of tokens according to compute-optimal criteria: for the same calculation it is better to use smaller models trained on many more tokens rather than huge models on a few data, with a rule of thumb close to ~ 20 tokens per parameter; on this basis, the Chinchilla model (~ 70B parameters, 1.4 trillion tokens) systematically outperforms much larger but under-trained models in zero-few-shot and in many comprehension and reasoning benchmarks, even at comparable training calculation. The practical implication is that "today" LLM-type AI improves not only by increasing parameters, but above all by increasing pre-training data to the optimal point, with benefits in accuracy, cost efficiency and generalization (Hoffmann, et al.,2022).

"Hallucinations" in language generation systems are outputs that are not faithful or non-factual with respect to the sources or knowledge of the world, and can take on intrinsic , contradictions or distortions, with respect to the input and extrinsic ,unsupported additions forms, with different manifestations in abstractive summarization, dialogue, data-to-text, translation, generative Q&A and vision-language; the survey maps causes incomplete or noisy data, out-of-domain generalization, excessively "creative" decoding, model overconfidence, evaluation metrics and mitigation strategies along the entire cycle: pre-training, in-training, decoding the authors point out that no single metric fully captures fidelity across all tasks and that, in open-world scenarios, hallucination control requires combinations of techniques, human evaluation and traceability of sources. (Ji, Z. et al., 2023).

The Retrieval-Augmented Generation (RAG) paradigm combines the "parametric memory" of a pre-trained “seq-to-seq model” (BART) with a "non-parametric memory" made of indexed documents that are retrieved at runtime via a dense retriever; the generator conditions the output on the “top-k” more relevant passages, marginalizing the probability of the answer on the set of documents retrieved. The authors present two variants, RAG-Sequence and RAG-Token, and show

that the system can be trained end-to-end and updated by simply refreshing the index, without re-pretraining the model. On knowledge-intensive tasks, RAG achieves strong improvements over purely parameterized models and retrieve then read pipelines, thanks to more well-founded and traceable generations. However, practical limitations remain, retriever quality becomes a bottleneck caused by missing documents, latency increases with k and index size, and in domains outside Wikipedia you need well-kept and updated corpora (Lewis, P. et al., 2020).

InstructGPT shows that large language models can be made more useful and aligned with human instructions with a three-step pipeline: supervised fine-tuning (SFT) on proofs written by human annotators, training a reward model from preference comparisons between pairs of model responses, and reinforcement learning from human feedback, in which the model is optimized to maximize the reward model's score while remaining close to the pre-trained model. In human evaluations on real prompts, InstructGPT's responses show improvements in terms of adherence to instructions, veracity and reduction of unwanted content, although slight regressions may occur on some automatic benchmarks compared to the original model. The authors point out limitations and risks: the method critically depends on the quality of human feedback, there is a danger of over-optimization on the reward model, and the costs and time of collecting feedback can be significant; for this reason, they propose iterative updates of the reward model and methodological precautions in deployment (Ouyang, L. et al., 2022).

The Contrastive Language-Image Pre-training (CLIP) model learns transferable visual representations using natural language supervision: two encoders, images and text, are trained with a contrastive lens on a web-scale dataset of ~ 400 million image-text pairs, learning to associate each image with the correct caption; at the test, just "describe" the classes with prompts and the model performs zero-shot classification building a classifier from textual embeddings, without any fine-tuning on the downstream dataset. The authors show competitive zero-shot transfer across more than 30 datasets and robustness to distribution changes superior to supervised models of equal accuracy (Radford, A. et al., 2021).

Typical consulting activities are summarized in ten ways: providing information, making specialized resources available, creating business contacts and connections, offering expert opinions, carrying out diagnoses, developing proposals for action, developing systems and methods, planning and managing organizational change, training and developing management and staff, and counselling and coaching. The functions of the consultancy are organized in five phases: entry, diagnosis, action planning, implementation and termination. In terms of behavioural roles, the consultant can operate as a collaborator in the solution of problems, an identifier of alternatives, a

trainer or educator, a technical expert, an advocate, a fact finder, a process specialist and a reflector. As for the skills required, the volume emphasizes skills in diagnosis and problem solving, planning, project management and evaluation, as well as communication and teamwork; it also calls for updates on behavioural and process consulting skills and on sharing reliability, versatility and initiative are emphasised for administrative support staff, along with technical expertise and discretion (Kubr, M. 2002).

As Professional Service Firms (PSFs), they are characterized by high knowledge intensity, low capital intensity and professionalized workforce, resulting in organizational structures centred on professional autonomy and reputation (Von Nordenflycht, A. 2010).

Common functions combine client-facing lines with internal enabling functions such as customer relationship management, HR, knowledge management, and quality control (Empson, L. et al., 2015).

In the Oxford Handbook of Professional Service Firms, PSFs are described as organizations that offer knowledge-intensive and "tailored" services, knowledge-rich, time-sensitive advice, with high contextual sensitivity and strong relational embeddedness, factors that limit standardization and commoditization of processes. Since the main assets are people and customer relationships, specific complexities emerge in customer relationship management and human resource management, in contexts where power is widespread among independent professionals and management is more consensual. The book also outlines some essential cross-cutting elements and functions for PSFs like strategy, client relationships, and HR practices and discusses issues such as outsourcing and offshoring of professional work (Empson, L. et al., 2015).

Performance in professional innovation brokerage services by comparing technology consultants and management consultants: identify three drivers focus on the customer, innovativeness and ability to learn of practice, and find that, for technology consultants, innovativeness and learning performance improves, while for management consultants these two factors are not relevant and the focus on the client is decisive (Williams, C., & van Triest, S. 2023).

In the context of Professional Service Firms, Fu, Flood, Rousseau, Morris and Johnstone (2023) analyse when client engagement really helps projects: with a multi-level analysis of 58 project managers and 171 consultants nested in teams, they find that client involvement is associated with better team performance and greater creativity of members' ideas; however, these effects depend on the level of team bonding capital when cohesion is high, the positive impact of customer engagement increases; when it is low, engagement does not improve performance and can inhibit individual creativity. A practical indication emerges: to capitalize on co-design with the client, it is

necessary to build strong team relationships that facilitate communication, trust and effective decisions (Fu, N. et al., 2023).

The research investigates, through online surveys of small consulting firms in Central Italy, what marketing and communication practices management consulting firms adopt and how they manage the relationship with customers: about half of the sample declares that they carry out marketing and communication activities mainly by leveraging websites and social media, as well as brochures and participation as a speaker at conferences; the maintenance of the relationship takes place with individual meetings, newsletters and periodic phone calls (Gabbianelli, L., & Pencarelli, T. 2020).

2. Theoretical Background and Hypotheses

2.1. Human–AI Collaboration and Job Substitutability: A Literature Review on Task Content and Work Design

The current chapter develops a theoretical background and the literature review of this thesis, with the aim to clarify which job activities characteristics and organizational contexts make a professional role more or less expose to the risk of AI-driven job substitution. In particular, it addresses the main task-based strands on automation and technological change, focusing on the dimensions like standardization of the tasks, as well as on attributes that reduce substitutability, such as novelty and ambiguity of tasks and the demand for relational skills. Alongside this, contributions on human-AI collaboration and the jagged frontier are discussed, as well as evidence on organizational and contextual factors like time pressure, error consequences, bias and reliance on algorithmic outputs, and privacy and data protection constraints, which affect the adoption and governance of AI and, indirectly, the perception of substitutability. On the basis of this framework, the literature review allows to derive in a coherent way the research hypotheses, which will be presented in the next section and subsequently subjected to empirical verification.

2.1.1. Human–AI Collaboration: Augmentation, Performance Gains, and Governance Challenges

Based on a qualitative design, GenAI's impact on the business model of management consultancy services: they adopt a qualitative content analysis of 15 interviews with consultants from different firms and derive subcategories along three dimensions, value creation, value proposition, and value capture, to map where and how generative AI works. The evidence collected shows that GenAI increases the efficiency of processes, automates routine tasks and optimizes knowledge management, allowing consultants to reallocate time to tasks with greater creative value; opportunities also emerge to reduce costs and new revenue streams, accompanied by additional challenges that require organizational shrewdness. A transversal result is that the relationship with the customer and human insights remain central: GenAI is perceived as a strategic complement, not as a substitute for the consultant. On a methodological level, the approach based on multiple interviews and thematic coding allows to highlight recurring patterns in adoption practices and impacts on the business model, while maintaining the exploratory nature typical of case-based studies (Tronnier, F. et al., 2025).

The adoption of AI in large auditing firms, based on 22 interviews with professionals from the major networks and document that the current use is mostly of augmentation of processes such as

machine learning for anomaly detection and matching, natural language processing and optical character recognition for contract and leasing reviews, analytics for testing on complete populations and automated confirmations, while cases of complete automation and the systematic use of GenAI remain experimental and under strong human supervision. The main critical issues that emerged concern transparency and explainability of models, bias, data privacy, robustness and the behavioural risk of auditors' over-reliance on algorithmic outputs; in addition to this, there is regulatory uncertainty and the need for governance and internal policies adequate for the use of data and models. Overall, the study concludes that the operational benefits are concrete, but conditioned by technological maturity, data quality, staff skills and control structure: without sufficient explainability and ethical-regulatory safeguards, adoption on "core" assurance tasks remains prudent and gradual. (Kokina, J. et al., 2025, Yang, J. et al., 2024)

An experimental study analyses two pre-registered randomized experiments involving two pre-registered randomized experiments with 758 BCG consultants assigned to three conditions, no AI, GPT-4, GPT-4 +, overview of prompt engineering to perform 18 realistic tasks typical of consulting work; "within the frontier" AI produces significant causal improvements: participants with access to GPT-4 complete 12.2% more tasks, are 25.1% faster and obtain > 40% higher quality (human assessments), with an average effect of +46.6% in aggregate specifications and more marked advantages in the arm GPT-4 + overview; the less experienced reap the greatest benefits. From the observation of behaviours, two patterns of effective use emerge: the "Centaurs", who consciously divide the phases of work between themselves and the model, and the "Cyborgs", who closely integrate AI into the operational flow with continuous interactions. Overall, the "jagged frontier" implies that AI offers large gains on some workflow steps, but can degrade performance on others, requiring task selection, human-AI process design, and governance adequate (Dell'Acqua, F. et al., 2023).

2.1.2. Task Standardization and Substitutability

The author Autor, Levy & Murnane (2003) in their elaborate have studied as task standardization coincides with the routine of the job components, an activity is more substitutable when it can be run through specific rules e repetitive procedures because the IT capital is particularly effective in executing procedural logics. Consequently, computerization tends to substitute human work in routine tasks, both cognitive and manual, while it is complementary when the task requires problem solving and complex communication.

In the contribution of Erik Brynjolfsson, Tom Mitchell and Daniel Rock (2018), the "standardization" covers a central role because it increases the "Suitability for Machine Learning" (SML), activities can be more substitutable when input and output are measurable and observable so, the machine could learn to map the activities and run it. Following the approach, routine tasks tend, typically, to generate traceability and clean metrics, making them easier to be managed by computers. In Carl Benedikt Frey e Michael A. Osborne (2017) framework link technological substitutability to the structure of the tasks that make up an occupation, the more activities are, repetitive and carried out in predictable contexts, the more plausible it is that they will be computerized. Thiers methodologies estimate a positive "computerization probability".

2.1.3. Empathy and Negotiation as Barriers to Automation

In the framework of Carl Benedikt Frey e Michael A. Osborne (2017) tasks that require empathy and negotiation fall within the activities with high social intelligence, considered a true bottleneck for automatization process, several roles become less appetible to the computerization when they depend on ability like to comprehend other people's reaction or to persuade, because technologies suffers to recognise feeling in real time, in particular to elaborate contextualized and coherent answers in complex human interactions. Cognitive and relational capacity are associated to a factor of resilience to the computerization.

In Deming, D. J. (2017). study, tasks that require empathy and negotiation are interpreted as components of social skills, they result less substitutable by digital technologies because computer are still "weak" to simulate complex human interactions and to manage implicit signals. Conflicts and building trust. Coherent with this idea, the author highlights how job positions requiring social skills have a higher salary rather that other roles, particularly when social skills and cognitive skills coexist. The author proposes a team production model in which social skills can reduce coordination costs and employees can "change their tasks" to leverage their insight capabilities.

In the OECD employment outlook 2023, highlights that, close to technical competences connected to AI, transversal skills are becoming central in the social nature, comprehensive of teamwork and collaboration within the team, because they are more difficult to be replicated by Artificial Intelligence over the numerical skills. In this prospective, it implies that tasks that require empathy and negotiation features like relationship management, persuasion, coordination, reading the social context, compromises, are less "mappable" in explicit rules and therefore less exposed to direct substitution; more plausibly, AI acts as a support in preparing of arguments, synthesizing of information, suggesting, while the outcome still depends on human interaction.

2.1.4. Consequences of Errors, Trust, and Human Oversight

Automatization errors can't be totally eliminated and when they occur the human intervention has a critical importance for the system through a complex error management process composed by error detection, causes comprehension and correction. Furthermore, the author highlights that the efficacy of this approach is influenced by variable connected to technologies and to the operative situations which could be automation reliability, interface design, with direct implications on the consequences of error: when the automation fails, the negative impact can increase if the error is not intercepted and corrected. This goes to support to context in which the error's consequences are potentially elevated, the human presence capable to menage the automatization failures become fundamental, strengthening the necessity of supervision and mitigating the major Artificial intelligence involvement as complete substitute. (McBride, S. et al., 2014).

The errors made by an algorithm have behavioural consequences with relevant impact compared to the human's errors: when the algorithm fails, people tend to reject the algorithm usage for next activities following a more rapid loss of confidence in the algorithm, although the evidence state that the algorithm works better than humans. "Algorithm aversion" is described by the authors as expensive because it brings individuals to choose less accurate alternative so, to obtain results below the expectations. In terms of the literature on error consequences, a single algorithmic error can drastically reduce the acceptance of the tool, making it more difficult to assign it to tasks where the error is particularly relevant or visible. (Dietvorst, B. J. et al., 2015)

Artificial Intelligence is increasingly used in high-stakes contexts, the automation errors can bring to relevant consequences on the security plan, legal responsibility and ethic. Moreover, it concerns automation bias born from a poorly calibrated trust, when users assume that artificial intelligence operates without commits any error, the output critical evaluation decreases, and specially in highly workload periods, move the attention to other manual activities, increasing the risk of delay on the error detection. These errors can propagate into decision-making process, increasing verification effort and active user involvement are important to reduce complacency towards incorrect Artificial Intelligence recommendations (Romeo, G., & Conti, D. 2025).

2.1.5. Privacy Requirements and Constraints on Artificial Intelligence Use

Users' Information Privacy Concerns (IUIPC) was validated e proposed by Malhotra, Kim & Agarwal to explain how topics linked to confidentiality and privacy requirements influence the consumer behaviour related to the disclosure and online use of personal data. In particular, the privacy is how a multidimensional construct composed by concern about the amount of data

collected, desire to maintain control over how data is used and disseminated, and awareness and information about data processing practices. Moreover, the authors show that high level of IUIPC are associated to unfavorable evaluations with respect to the disclosure of personal information and affect behavioral intentions to share data when requested by third parties, thus highlighting that perceptions of privacy and data control represent a key driver in the acceptance and use of technologies that process personal information for use. (Dinev & Hart, 2006; Malhotra et al., 2004)

The principal challenges in terms of ethics and trust on the GenAI adoption are explicitly privacy and data protection with themes like transparency, accountability and misuse risk. From the collected data emerges emerges in a very concrete way that, precisely because of fears related to confidentiality and data protection, some organizations declare the confidential data provided by the users will not pass through public domain GenAI platforms, this would increase the exposure to leakage and violations. Moreover, the discussion connects the privacy issue directly to implementation limits: data protection regulations that make it more complex to use GenAI when processing sensitive data, requiring consent and additional compliance measures, blocking its adoption. (Hughes, L. et al., 2025)

In the “age of information”, to interface with digital technologies leaves traces of data which can bring to the light, characteristics and intentions of their users, in this way the privacy cover a central role in the decision-making process related to sensible data sharing. The key points that the authors highlight: individual uncertainty on the future consequences of misuse of their personal data strong deadened from technologies, warning about privacy themes. The usage of date-intensive technologies doesn’t only depend on technical aspects, but on behavioural factors and contextual as well, which influence the consumer to accept or not to share their sensitive data (Acquisti, A. et al., 2015).

2.1.6. Time Pressure and Reliance on AI Support Systems

Time pressure in human-AI collaboration does not affect the behaviour homogeneously but is influenced by the moment in which it is imposed in the decision-making process. The authors highlight that the effect of time pressure is task-dependent mainly in the initial phase, while time in the final phase significantly influences the integration of the AI suggestion: in fact, those who use AI-based technological tools are more likely to follow the AI's recommendations when they have more time in the final decision phase. In work environments with tight deadlines and deliveries, time management at different stages of production and review can change how much professionals rely on AI assistance to close the job. (Cao, S. et al., 2023)

The pressure on the delivery times to respect not negotiable deadlines is a critic factor in decision-making contexts. When the time to complete a task is tight and there aren't any alternative options, the quality of the decision tends inevitably worsen by limiting the analysis and in-depth review of information and evidence. Despite this, the study shows that using an automated decision support system (DSS) can mitigate the negative effects of time pressure, supporting the users through the decision-making process, however this dynamic affects, also, the way in which people handle the relationship with technology, influencing the reliance on DSS, especially during period of work more frenetic (Rieger, T., & Manzey, D. 2024).

The automation bias in presence of decision support system (DSS), concerns the tendency to excessively to follow the recommendations of technology, when these result wrong or when the control over the technology is necessary as well. The authors underline that such risk intensifies in condition which stress the individual's cognitive resources as the need to quickly deliver output while meeting deadlines pushes to reduce checks and rely on DSS as a shortcut to speed up the decision-making process. In this way, the time pressure related to the deliverables can foster the overuse of the technology and minor propensity to control the automated advice (Goddard, K. et al., 2012).

2.1.7. Task Novelty and Ambiguity: Limits to Full Automation

Information technologies are increasingly replacing human labour, especially when it comes to repetitive and routine tasks, those that can be carried out by following precise instructions and well-defined procedures. However, as the authors point out, automation works differently for non-routine activities: here technology does not replace the human being but supports him. We are talking about those tasks that require the ability to solve unexpected problems, to adapt to ever-changing situations and to manage articulated communications. From this point of view, when we are faced with unprecedented situations, where there are no standard procedures or clear instructions to follow, technology struggles to replicate that capacity for judgment and interpretation that comes naturally to human being, and this is precisely what makes certain jobs more resistant to the risk of automation. (Autor, D. H. et al., 2003)

When we are faced with complex, unprecedented or unclear tasks, artificial intelligence works better as a collaborator than as a substitute. The reason is simple: this type of activity requires the ability to interpret, evaluate and adapt to the context, typically human qualities. The authors propose an interesting model, called the "automation–augmentation paradox", which highlights a

fundamental aspect: automation and augmentation are not two opposite paths to choose from, but are closely linked to each other. In this perspective, precisely in cases where work is new and ambiguous, organizations tend to prefer hybrid solutions where man and machine collaborate. AI can make some steps in the process more efficient, but it's the person who stays at the centre when it comes to handling unexpected situations, making sense of piecemeal information, or making decisions when you're uncertain (Raisch, S., & Krakowski, S. 2021).

Tasks that present a high degree of novelty and ambiguity are less at risk of being completely replaced by technology than standardized and repetitive ones. Digital technologies capable of imitating human work are in fact able to replace us more easily in activities that can be "translated into code" and that follow predictable patterns. But they find it difficult when the job requires skills that represent real obstacles to computerization. In particular, there are three skills that remain difficult to automate: creativity, social intelligence and the ability to perceive and interpret unstructured situations. These skills are typical of those new and ambiguous tasks because they require understanding the context, knowing how to adapt when things do not go as planned and working even when the information available is incomplete or unclear. (Brynjolfsson, E. et al., 2018).

2.1.8. Artificial Intelligence Adoption in Practice: Usage Intensity and Employee AI Competence

The Microsoft Work Trend Index 2025 and the PwC Global Workforce Hopes and Fears Survey 2024 outline a convergent picture in which artificial intelligence, with particular reference to GenAI, is configured as an enabling technology now increasingly integrated into daily work activities, especially in support of recurring knowledge micro-processes. In this perspective, artificial intelligence is mainly interpreted as a lever for efficiency and reallocation of cognitive resources towards activities with greater interpretative and creative intensity, rather than as an automatic replacement mechanism. However, both sources highlight that the full capture of benefits is conditional on the adoption of complementary skills like critical evaluation of outputs, supervision, integration into decision-making processes, and the organizational ability to incorporate AI into workflows. Consistently, PwC indicates that recurring adoption is still relatively low, about 16% of its employees declare at least weekly use, but among users there are significant perceived benefits in terms of time efficiency, 61% of its employees report an increase, while the main barriers are attributable to organizational and capability constraints. Overall, this evidence supports the argument that the impact of AI on work depends crucially on process design, targeted

upskilling and adequate governance safeguards aimed at guiding its effective and controlled use (Microsoft, 2025; PwC, 2024).

In the contribution Beyond the hype: Organisational adoption of Generative AI through the lens of the TOE framework, it emerges that the availability of internal skills is an enabling condition for the effective adoption of GenAI: integration requires a high level of technical expertise and involves a significant learning curve, especially in functions with little previous experience in advanced AI technologies. In this perspective, respondents highlight a frequent skills gap: management may be attracted by potential efficiency and cost gains, but tends to underestimate training and upskilling needs, leaving employees less prepared to incorporate tools into daily workflows. The article also points out "skill-related" risks on the human capital side, such as the possible over-reliance of junior profiles, but at the same time the need for retraining and repurposing to accompany the transition. It follows that "competence" is not only technical, but also includes training in responsible use, governance, human control, awareness of limits, while the organizational ability to learn and disseminate knowledge can transform individual skills into shared routines (Hughes, L. et al., 2025).

2.2. Research Gap and Research Question

Despite the growing academic interest of the impact of AI in the workforce, research on the topic remains relatively nascent. Until recently, most research has focused on understanding the emergence of Artificial Intelligence and identifying the primary drivers behind their rapid growth, typically investigating which factors made this new technology appetible for company to achieve greater efficiency level as performance benchmark (Devlin, et al., 2018). However, this approach ignores the heterogeneity in activities within the same firm.

This internal divergence suggests the need to understand what makes some function more exposed than others. Furthermore, due to the previously limited number of available studies, existing literature has predominantly relied on audit firms and their activities (Yang, J. et al., 2024, Kokina, J. et al., 2025). The quantitative studies tend to concentrate on drivers of growth and efficiency of economic results rather than the effect on the customer’s perception of the firm.

As a result, there is an underdeveloped academic gap concerning how much actual employees are effectively exposed, based on their function. Specifically, it remains unclear which drivers can explain why, even amidst this vague idea of a technology capable of anything. Addressing this gap

requires shifting the focus from the emergence of exposure to a more in-depth exploration of the perceived risk of replacement.

Therefore, in light of this gap, a well-defined research question is proposed:

"How the characteristics of work activities performed within the Professional Services Firms (PSFs) influence the perceived risk of human being replaced by AI-based technologies"

2.3. Hypotheses

This segment will put six primary hypotheses about activities and their effects on the Artificial intelligence adoption within professional service firms according to the research framework developed previously. These hypotheses are drawn from the theoretical concepts presented in the earlier segment and are specifically linked to the role of the activities characteristics in shaping the exposure of actual professional roles.

2.3.1. Task Standardization and perceived risk of AI-driven job substitution

From Operational definition, the authors define as "routine" tasks that can be codified with explicit rules and stable verification criteria; this standardization makes work replaceable by computers and automation technologies that in fact systematically replace routine tasks whether they are cognitive or manual and complement the non-routine analytical tasks (Autor, D. H. et al., 2003).

One criteria for task SML is that the set of inputs and the corresponding set of outputs for the task can be measured sufficiently so that these data can be effectively processed by tools capable of analysing them (Brynjolfsson, E., Mitchell, T., & Rock, D. 2018). Frey, C. B., & Osborne, M. A. (2017), define tasks with clear rules, predictable states and low variability as more automatable, therefore standardizable and translatable into well-structured processes that can be easily transmitted to a computer.

The most exposed jobs are those consisting of routine tasks with clear and verifiable steps "tasks following well-defined procedures". In other words, when the procedure is standardized, technological substitutability increases, Recent advances aim precisely at standardizing the ambiguous, "turn non-routine tasks into well-defined problems", making previously unstructured segments automatable (Frey, C. B., & Osborne, M. A. (2017)

Building on these insights, the following hypothesis is proposed:

H1: When tasks are standardizable and codifiable, they are linked to a greater probability that the activity can be run by technologies based on artificial intelligence.

2.3.2. Empathy and Negotiation Skills Required by the Task and perceived risk of AI-driven job substitution

The author Deming, D. J. (2017) highlights the difficulty of automating tasks in which human interaction plays a central role that, while computers perform increasingly complex cognitive tasks, simple human interaction remains "difficult to automate", signalling the low substitutability of tasks for empathy and negotiation

His analysis shows that employment and wages have grown "for jobs requiring high levels of both math skill and social skill", indicating that roles that combine analysis and relationship, complementarity with cognitive skills, achieve the greatest returns.

Human social intelligence is important in a wide range of work tasks, such as those involving negotiation, persuasion and care stating that negotiation and elements of empathy and care as key components that cannot be automated (Frey, C. B., & Osborne, M. A. 2017)

As highlighted by the authors Frey, C. B., & Osborne, M. A (2017) the real-time recognition of natural human emotion remains a challenging problem, and the ability to respond coherently to such inputs is even more difficult. Therefore, recognizing emotions and responding appropriately remain bottlenecks for AI, making occupations that involve social intelligence tasks unlikely to be substituted by computer capital

According to the Organization for Economic Co-operation and Development, transversal skills such as social skills are not codifiable stating that, precisely where human interaction is central, AI tends to integrate rather than replace, these skills are harder to replicate by automation technologies. The report points out effects on the social dimension of work and the limitations of AI in human interactions that reducing the social dimension of work can generate an isolation feeling among workers and, although systems are being developed to capture non-verbal cues, the quality of human interaction remains a policy issue. This reinforces the idea that activities grounded in empathy and negotiation maintain a human advantage (OECD. 2023).

Building on these insights, the following hypothesis is proposed:

H2: Tasks that requires high grade of empathy and negotiation are unlikely to be substituted by the Artificial Intelligence

2.3.3. Severity of Error Consequences and perceived risk of AI-driven job substitution

When the consequences of an error are high, McBride, Rogers and Fisk (2014) point out that human presence becomes central because automation errors cannot be completely eliminated and, precisely in the most critical cases, the system depends on the intervention of people to quickly intercept the problem, understand its origin and correct it. In other words, the more it "costs" to make mistakes, the more active human control is needed to ensure reliability and reduce the negative impact of automation errors.

According to Dietvorst, Simmons and Massey (2015), when an algorithm makes a mistake people tend to lose confidence very quickly and to refuse to use the tool even though, on average, the algorithm may be more accurate than a human. This means that, in tasks where the error is particularly relevant or visible, the possibility of algorithmic failure makes it more difficult to fully delegate the decision to technology and reinforces the importance of human judgment, which remains necessary to protect the quality and reliability of the final outcome.

Finally, Romeo and Conti (2025) highlight that AI is increasingly being used in high-stakes contexts, where a mistake can have significant consequences in terms of safety, ethics and legal liability.

Precisely in these scenarios, the authors recall the risk of automation bias: if users assume that AI "does not make mistakes", they reduce the critical evaluation of the output and may notice errors late. As a result, when the consequences are high, the need for a stronger human role, based on active verification and constant supervision, grows to prevent an AI error from spreading and producing greater damage

Building on these insights, the following hypothesis is proposed:

H3: When the consequences deriving from an error are more serious, we tend to prefer to maintain a greater involvement of human resources performing the task

2.3.4. Data Confidentiality and Privacy Requirements and perceived risk of AI-driven job substitution

Malhotra, Kim and Agarwal (2004) show that high privacy concerns, in terms of the amount of data collected, control over the use and dissemination of information and awareness of processing practices, reduce the willingness to share data with third parties; consequently, more stringent privacy requirements make the use of data-intensive technologies less easy and therefore an extended replacement by AI less plausible.

Hughes et al., (2025) highlight that privacy and data protection are among the main critical issues of GenAI adoption: many organizations avoid transiting confidential information on platforms for public use to reduce the risk of leakage and breaches, while regulatory constraints on sensitive data require additional compliance measures, concretely limiting the implementation and automation of processes.

Acquisti, Brandimarte and Loewenstein (2015) point out that digital technologies generate information traces and that privacy concerns are strongly contextual and linked to uncertainty about the future consequences of data use; when the context requires high confidentiality and perceived risks increase, caution grows towards data-intensive tools, helping to limit the adoption of AI and reduce the perceived risk of substitution.

Building on these insights, the following hypothesis is proposed:

H4: Increased data privacy and confidentiality requirements reduce the perceived risk of Artificial Intelligence substitution.

2.3.5. Time Pressure on Deliverables and perceived risk of AI-driven job substitution

When deadlines are tight and you must deliver quickly, the literature shows that the quality of decisions tends to deteriorate because the time available to analyse and verify information decreases. In this scenario, automated decision support tools become particularly "attractive" because they help you keep up with the pace and close work faster. Precisely because technology becomes an increasingly central support under pressure, it is plausible that workers perceive a greater risk of substitution, especially for the parts of the job that are more standardizable. (Dinev & Hart, 2006; Malhotra et al.,2004)

Goddard, K., et al., (2012) systematic review of automation bias shows that factors that stress cognitive resources, including time pressure, can push users towards a more intense use of automated systems, reducing the propensity to critically control the output. In other words, when time is lacking, technology is experienced as a useful shortcut to get to the deliverable: this can reinforce the idea that, in contexts of high time pressure, AI is not just a support but can become a substitute to speed up the completion of work.

Finally, studies on human-AI collaboration show that the time available in the different phases of work concretely influences how much you rely on AI assistance to arrive at the final decision. In a context of tight deliveries, AI tends to be used as a lever to reduce production and review times, and this can turn into a very direct perception: if the technology allows for faster delivery, then there is a growing fear that a growing part of the human contribution is "replaceable", increasing the perceived risk of replacement. (Acquisti, A., et al., 2015)

Building on these insights, the following hypothesis is proposed:

H5: Increasing time pressures on outputs increase the perceived risk of Artificial Intelligence substitution.

2.3.6. Task Novelty and Ambiguity and perceived risk of AI-driven job substitution

Autor, Levy and Murnane (2003) point out that information technologies are more likely to replace routine activities, while they become less effective when the work is non-routine. In particular, when a task is new and ambiguous, there are no stable procedures and explicit rules to follow: problem solving, interpretation and adaptation to the context are needed. Precisely for this reason, the more the novelty and ambiguity of the task increases, the more the possibility that the technology will replace it completely decreases, and therefore the perceived risk of substitution tends to be reduced.

Raisch, S. and Krakowski, S. (2021) argue that in complex, new and ambiguous tasks, artificial intelligence works better as a support than as a total replacement, because execution requires judgment and the ability to handle uncertain situations. In their "automation–augmentation paradox", the authors show that in these contexts the organization tends to prefer hybrid human-machine configurations, in which AI helps in some phases, but the human contribution remains

decisive for interpreting incomplete information and handling exceptions. As a result, the more ambiguous and newer the task, the less credible a complete replacement is and the more the perceived risk of replacement is mitigated.

Brynjolfsson, Mitchell and Rock (2018) point out that the impact of AI is mainly focused on the most codable and repetitive components of work, while it encounters limits when activities require skills that are difficult to replicate, such as creativity, social intelligence and management of unstructured contexts. These characteristics are typical of tasks with high novelty and ambiguity, where new situations must be interpreted and exceptions must be addressed. In this sense, the newer and more ambiguous a task is, the less likely it is to be fully automated, reducing the perceived risk of replacement.

Building on these insights, the following hypothesis is proposed:

H6: Higher levels novelty and ambiguity within the tasks are associated with a lower perceived risk of AI-driven job substitution.

3. Methodology

This chapter outlines the research methodology adopted in this study. Specifically, it presents the characteristics of the sample, the variables employed, and the econometric models implemented to test the research hypotheses.

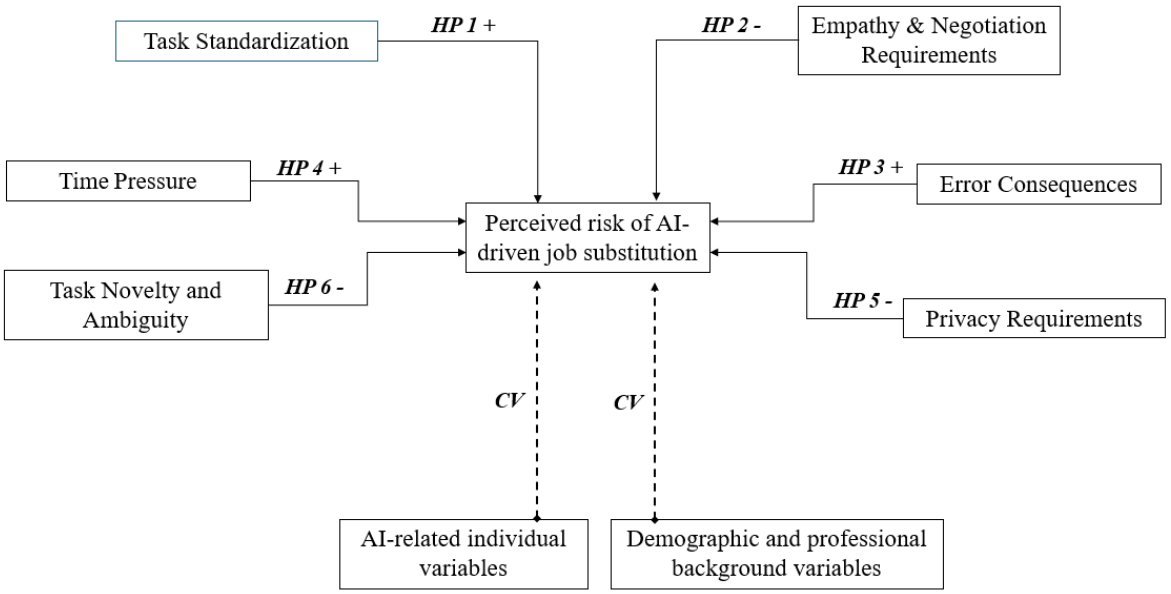
3.1. Research Setting

As anticipated in the previous chapterr, the current study aims to investigate the factors which determine the perceived risk of AI-driven job substitution, with a specific attention on the role of task characteristics and the individual variables influencing such perception. The analysis has been conducted thought the collection of primary data on behalf of a questionnaire, presented to the Professional Service firm employees, comprehensive of profiles who go from the entry-level position to the managerial and directive positions. The heterogeneity of the sample consents to seize several perspectives related to the Artificial intelligence within the daily activities, including both operative roles and decision-making roles. The variety of the represented roles makes so to obtain an articulated view of the phenomenon. The objective of this analysis is to reply to the following question: How the characteristics of work activities performed in Professional Services Firms (PSFs) influence the perceived risk of human being replaced by AI-based technologies?

3.2. Data Collection

The study adopts a quantitative research approach aimed to provide- a structured, systematic, and objective examination of the research question, generating measurable empirical evidence related to the phenomena under investigation. The analysis is grounded in the conceptual model presented in Figure 1 and is structured around the six hypotheses developed in the previous chapter, which guide both the empirical design and the interpretation of the results.

Fig. 1 – Complete Research Model



The research model proposes an explanatory framework in which the perceived risk of job replacement by AI represents the central employee variable, influenced by six determinants related to job content. In line with the task-based approach, the model hypothesizes a positive effect of task standardization (HP1) and time pressure (HP4), suggesting that more routine activities carried out in high-urgency contexts are perceived as more replaceable. On the other side, a negative effect is assumed for activities that require empathy and negotiation (HP2) and for those characterized by novelty and ambiguity (HP6), considered less codified and therefore less exposed to technological substitution. The consequences of error (HP3) are expected to have a positive effect, as in contexts of high error relevance, AI can be seen both as a support and as a potential substitute, while privacy requirements (HP5) are hypothesized to have a negative effect, as information constraints can limit its automation. The model also includes two blocks of control variables, AI-related individual characteristics and demographic and occupational variables, that directly affect the dependent variable, in order to isolate the net effect of the task characteristics. Overall, the structure reflects a coherent theoretical framework that integrates technological, organizational and individual dimensions in the explanation of the perception of substitutability.

The data were collected from an ad hoc questionnaire, designed to respond in a timely manner to the previously defined research question. During the design phase of the instrument, the first decision concerned the choice of the most suitable measurement scale to evaluate and quantify the selected variables characteristics of the tasks, organizational factors, exposure outcomes. In the questionnaire

used for the current research, Likert scales of different authors were adopted, in line with the reference literature from which the measurement tools were taken. In particular, the variables analysed were measured through 5-, 6- and 7-point Likert scales, depending on the scale originally validated in previous studies. This choice allows to preserve methodological consistency with existing theoretical contributions and to maintain the psychometric properties of the scales used, avoiding arbitrary changes that could compromise the reliability and validity of the measurements. This choice is consistent with recent applications in large tech organizations and in evaluations of professional roles.

The questionnaire is aimed at employees of any level of seniority, from entry-level to top management, employed by Professional Service Firms (PSF) operating in the management consulting sector.

In particular, the perimeter includes: (i) the Big Four: Deloitte, PwC (PricewaterhouseCoopers), EY (Ernst & Young) and KPMG; (ii) the main strategic consulting firms (MBB: McKinsey & Company, Boston Consulting Group, Bain & Company); (iii) consulting boutiques that meet a minimum size requirement of at least 1,000 office-level employees. This delimitation ensures organisational homogeneity and comparability of results in contexts characterised by complex structures, articulated service portfolios and sufficiently standardised internal processes, a necessary condition for reliably estimating exposure to AI integration across differentiated functions and career paths.

The questionnaire is structured in two sections consistent with the measurement objectives. The first section is dedicated to the collection of the respondent's socio-professional information like level of seniority, function, office size, necessary for the control of heterogeneities and for the use of the related controls in empirical models. The second section presents the operational items aimed at measuring the variables of interest, independent, moderator and dependent , with questions formulated on Likert and dichotomous scales to capture, among others, standardization and repetitiveness of tasks, intensity of texts and data, empathy and negotiation requirements, IT policy and integration, AI training and AI exposure and risk index. The items are derived from the literature, written in a unique form and ordered to minimize response bias, so as to ensure the validity of the content and reliability of the measures.

The questionnaire was implemented using Microsoft Forms, and the responses were collected and examined directly from the same channel.

3.2.1. Measurement Scales

The variables considered within this study are articulated in three categories: dependent varible, six independent variables and control variables. The measurement of the constructs has been carried out through the measurement scales already validated in previous contributions published on relevant international journals, with the aim to guarantee reliability and fitness for analysis. The dependent variable concerns the perceived risk of replacement by technologies based on artificial intelligence of employees in Professional Service Firms studied through the daily activity's characteristics. The scale was adapted in wording, when necessary and according to the goals of the study, from the article by Tong, H. et al., (2025), some examples of the scale are : *I am worried that AI will replace my work in the future, I feel anxious working with AI that is smarter than me, I'm worried that AI will replace many people's work.* The operationalization scale analyses the perceived risk of occupational substitution attributed to artificial intelligence, intercepting both an individual dimension and a broader dimension of social concern, as well as an affective component linked to interaction with advanced systems. The first item measures the prospective personal concern about the possibility that AI will replace one's job in the medium to long term; the second item measures a specific emotional reaction, the anxiety associated with collaboration with an AI perceived as "smarter", attributable to fears of reduced autonomy, loss of control or devaluation of skills; the third item extends the object of evaluation to the macro level, investigating concern about the substitutability of human labour in general and potential systemic employment implications. Overall, the scale allows to derive a synthetic indicator of job substitution anxiety and concern, integrating assessments of individual risk, emotional response and perception of the aggregate impact on employment.

Moving now to the six independents, they concern the characteristics of the daily activities run by employees, multiple scales selected from the articles published in the major journals are Bacharach, S. B. et al., (1990), Mamatoğlu, N., & Keskin, S. (2019). Rybowiak, V. et al., (1999), Edwards, J. A. et al., (2008), Malhotra, N. et al., (2004), Trommer, M. et al., (2021). Some examples of the scale are: *I have to make decisions, the consequences of which are uncertain, it is the most important thing to keep my privacy intact from online companies, I am pressured to work long hours, I speak to the other side face with eye contact in negotiation.* The scales reported operationalize, in a manner consistent with the literature on the task-based approach, some key dimensions of work content that may influence the perception of substitutability by AI. Firstly, the items on empathy and negotiation capture the relational and socio-interactive component of the activity (negotiation assertiveness, face-to-face communication, trust building), those requests for social intelligence and management of implicit signals that are difficult to codify. Secondly, the

items on task standardization measure the degree of formalization and organizational codability of the work (documented procedures, complete job description, explicit chain of command), which reflects how much the activity can be translated into rules and therefore potentially "automated". Finally, the items on the error and error anxiety dimension intercept the component of worry and stress related to the possibility of making mistakes, useful for representing how the management of operational uncertainty and the fear of consequences can affect the way people evaluate the reliability of processes and, more generally, the vulnerability of their work to forms of automation. Taken together, these measures make it possible to link the perception of risk not to abstract individual characteristics, but to observable properties of the job.

Regarding the control variables, the measurement scales used came from the articles of Trommer, M. et al., (2021). And Chiu, T. K. F. et al., (2025) some examples of the scale are: *I spent most of the time working with artificial intelligence, I used artificial intelligence to carry out most of my job functions, when using AI technology, I am not worried that I might press the wrong button and cause risks.* The AI_USE and AI_COMP control scales measure the degree to which AI is operationally used in daily work, asking respondents to indicate how much AI has actually been integrated into their activities. In particular, the items assess the overall intensity of use, the extent of use compared to the and the involvement of AI in decisions. Overall, the scale serves to capture the direct exposure and frequency or centrality of AI in work processes, to empirically control the fact that greater familiarity of use can influence the perception of the risk of substitution regardless of the characteristics of the task or the individual.

3.3. Studied Variables

This section presents the variables used in the empirical analysis. The section is structured into three sub-sections, each dedicated to a specific type of variables: dependent, independent, and control variables. All relevant data were collected from the database built by the shared survey and systematically organized into analytical variables, while all the analyses were conducted on the statistical software R-Studio. The dependent variable is tested against six key independent variables, while control variables are included to account for potential explicative alternative factors, based on the theoretical background.

3.3.1. Dependent Variable **Error! Bookmark not defined.**

The dependent variable of this analysis is the perceived risk of replacement (AI_RISK) by technologies based on artificial intelligence of employees in Professional Service Firms (PSFs),

understood as the combination of technical transferability of tasks and expected effectiveness of implementation under realistic operating conditions. Operationally, the perceived risk is measured through Likert-scale item surveys relating to standardization and repetitiveness of tasks, intensity of texts and data, empathy and negotiation requirements with the customer, as well as organizational readiness such as policy, training, IT integration, data quality and integrability. This indicator allows intra-company comparison between Strategy, Operations and PMO, Risk and Compliance, Corporate Finance, Tax and Legal lines, capturing structural differences in the task mix and complementary assets.

3.3.2. Independent Variables **Error! Bookmark not defined.**

The independent variables included in the regression analyses aim to capture the impact on Artificial intelligence exposure. Based on the theoretical background and the hypotheses developed in the previous chapter, in this section the independent variables will be presented in relation to the hypothesis against which they are tested.

Task standardization (TASK_STD) - Task standardization refers to the degree to which work activities are formalized, repetitive and regulated by predefined procedures and guidelines. In contexts characterized by high standardization, the operating methods are clearly defined and leave limited space for individual discretion. This variable was measured using a 6-point Likert scale (1 = very little; 6 = very much), in line with the original scale proposed in the literature.

Empathy and negotiation skills required by the task (EMP_NEG) - The variable empathy and negotiation skills required by the task measures the degree to which the performance of work activities requires relational, communicative and emotional skills, such as building trust, managing conflicts and negotiating with clients or counterparties. These skills are generally considered difficult to automate. The variable was measured using a 5-point Likert scale (1 = very little; 5 = very much).

Confidentiality and data privacy requirements (PRIV_REQ) - Confidentiality and data privacy requirements indicate the degree of sensitivity of the information processed in the performance of the tasks and the need to protect it from unauthorized access or misuse. Tasks with high confidentiality requirements tend to limit the adoption of automated technologies. This variable was measured using a 7-point Likert scale, with values ranging from "very little" to "very much".

Severity of the consequences deriving from any errors (ERR_CONS) - The severity of the consequences deriving from any errors represents the level of negative impact that an error in the

performance of activities can generate, in economic, legal, reputational or organizational terms. In high-responsibility activities, error takes on a particularly high importance. This variable was measured using a 5-point Likert scale, ranging from "very little" to "very much".

Time pressure on deliverables (TIME_PRES) - Time pressure on deliverables refers to the degree to which workers perceive tight time constraints and a high workload intensity in performing tasks. High time pressure can influence the adoption of efficiency-oriented technology tools. This variable was detected using a 5-point Likert scale, ranging from "very little" to "very much".

Novelty and ambiguity of tasks (TASK_NOV)- The novelty and ambiguity of tasks describe the degree to which work activities require the management of situations that are new, complex or without a single solution. Tasks characterized by high ambiguity require judgment, interpretation and problem-solving skills, typically associated with human contribution. The variable was measured via a 5-point Likert scale, with anchors ranging from "very little" to "very much".

3.3.3. Control Variables **Error! Bookmark not defined.**

When trying to understand which factors drive Artificial Intelligence implementation in the context of PSF, many are shown to impact the efficiency of the integration process. While these factors are not the focus of this study, they still must be accounted for to avoid excluding possible scenarios and impactful explanation for heterogeneity of professional roles. Therefore, the models include 2 different control variables groups regarding demographics characteristic and personal behaviours in front of newest technologies. All control variables are based on the theoretical background findings, and the relevant data was collected from the shared survey.

AI-related individual factors- The AI-related variables considered in this research include AI personal usage (AI_USE) and AI competences (AI_COMP), understood as potentially relevant individual factors in shaping respondents' perceptions. AI personal usage measures the frequency and intensity with which participants use AI-based tools in carrying out work activities; this variable was coded as a composite index calculated as the average of the dedicated items, detected by means of a 5-point Likert scale with anchors from "very little" to "very much". Similarly, AI competences detect the level of perceived skills in the use of AI like familiarity and confidence in the use of tools and has been coded as a composite index obtained as the average of the corresponding items, also measured through a 5-point Likert scale with anchors from "very little" to "very much".

Demographic and professional background variables- Some demographic and professional context variables were included in the questionnaire in order to describe the sample and check for any systematic differences between respondents. In particular, age, gender, years of work experience and function or department within the Professional Services Firm were recorded, including Audit and Assurance, Consulting or Advisory, Deals or Financial Advisory, Tax and Legal. The demographic variables were coded as follows: gender was coded as a categorical variable, assigning a numerical code to the different modes of response (woman, man, I prefer not to answer); the age was encoded as a continuous variable, entering a single numerical value corresponding to the age of the respondent(AGE); the years of (EXP_) work experience were coded as an ordinal variable, based on 3 predefined bands (1-5, 6-10, over 10); finally, the membership function (DEPT_) was encoded as a nominal variable via mutually exclusive categories and, where necessary for regression analysis, was transformed into dummy variables.

3.4. OLS Models

To empirically test the hypotheses, a series of multiple regression analyses were estimated using Ordinary Least Squares (OLS).

The models are structured to evaluate the relationship between the perceived risk of AI-driven job substitution, the dependent variable, and a set of organizational and task-related independent variables, while controlling for individual socio-demographic characteristics. Two linear regression models will be presented.

The first model (M1 – Base) is designed to provide a parsimonious specification and includes the set of socio-demographic control variables (age, gender, and experience) together with a first key organizational variable, namely task standardization (TASK_STD). This baseline model allows for an initial assessment of the relationship between task standardization and the perceived risk of AI substitution, while accounting for individual-level heterogeneity as well as industry fixed effects and clustered standard errors.

The second model (M2 – Full) extends the baseline specification by introducing the full set of theoretical constructs considered in this study, including, among others, empathy and negotiation requirements, error consequences, time pressure, privacy concerns, task novelty and ambiguity, AI usage, and AI-related skills, in addition to the socio-demographic controls already included. This full specification represents the main regression model of the analysis and allows for the assessment

of the joint effects of the organizational and task-related variables on the perceived risk of AI substitution, while accounting for potential confounding factors.

By first estimating a more parsimonious model, the analysis enables an understanding of the standalone effect of task standardization on perceived AI substitution risk in its simplest form. Subsequently, by adding the full set of constructs, the second model allows for an evaluation of whether this relationship remains robust once other relevant job and task characteristics related to AI exposure are taken into account.

After carefully describing the research methodology, the two regression models are presented.

3.4.1. Model M1 (Base)

Model 1 (Base). Table 4 presents the results of the first model which tests the standalone effect of the independent variable *TASK_STD* on the dependent variable *AI_RISK*. In particular, it evaluates the first hypothesis in a specification that includes socio-demographic controls such age, gender, and experience, while accounting for clustered standard errors.

3.4.2. Models M2 (Full)

Model M2 (Full). Table 5 reports the results of the full model specification, in which the independent variables (AI_RISK) is tested along with the complete set of control variables. This model serves as the core analytical specification, aiming to represent the combined effect of the predictors related to single activities characteristics in daily employee's tasks and to the perceived risk of replacement by Artificial Intelligence, taking into account the possible alternative explanations through sociodemographic controls. In the following model over the sociodemographic controls, all the variables previously presented are included; TASK_STD, EMP_NEG, ERR_CONS, TIME_PRES, PRIV_REQ, TASK_NOV, and the two control variables; AI_USE, AI_COMP.

4. Results and Discussion

In this chapter, the results of the statistical analyses are presented and discussed thoroughly in relation to the research hypotheses and the existing literature. Specifically, the chapter is divided into sections, one for descriptive statistics and one for the main regression analyses. Subsequently, a series of robustness analyses are introduced to assess the stability and reliability of the results, including alternative specifications and the exclusion of influential observations. Overall, this chapter aims to provide a comprehensive interpretation of the evidence, linking the quantitative results to the theoretical framework developed in the literature review.

4.1. Descriptive Statistics

Table 2. reports the main descriptive statistics of the study. Particularly, the table contains the minimum, maximum, median, and mean value for all variables; not only, but also standard deviation. For the dependent variable, the non-transformed version was selected since choosing the transformed variable would not be representative of the true observations in the sample. The responses to the Likert items were normalized at the textual level, eliminating superfluous spaces and correcting only certain typos.

Regarding the dependent variable AI_RISK, the descriptive statistics show a medium moderate level of perceived risk of replacement by AI (Mean= 2.745; Median = 2.667). The proximity between mean and median suggest a distribution substantively equilibrate without strong asymmetries, while the standard deviation is (SD= 0.707) indicating a moderated variability on the employee answers. The minimum value equal to 1 highlights the presence of interviewers who don’t perceive any replacement risk, while the maximum value equal to 4,667 highlights that, although a share of employees show a perceived high risk, such perceptions aren't predominant in the sample. Overall, descriptive data suggest that the perceived risk of AI substitution is present but not generalized, leaving room for significant heterogeneity in individual assessments.

Table 2. Descriptive Statistics

Variable	n°	Min	Median	Mean	Max	SD
AI_RISK	123	1	2.667	2.745	4.667	0.707
TASK_STD	123	2	4.6	4.505	6	0.884
EMP_NEG	123	1.333	3.667	3.657	4.667	0.741
ERR_CONS	123	2.333	4.3	4.145	5	0.562
TIME_PRES	123	2.333	4	3.982	5	0.637
PRIV_REQ	123	2.667	6.33	6.156	7	0.86
TASK_NOV	123	1	3.667	3.425	5	0.936
AI_USE	123	1	1.667	1.786	3.333	0.557
AI_COMP	123	1	2.333	2.454	3.667	0.472

Table 3. exhibits the correlation matrix. As opposed to the descriptive statistics, the dependent variable, AI_RISK, was used to ensure interpretability of the relationship between the variables used in the models.

Pearson's correlation matrix shows coherent and informative relationships between the variables considered. With reference to the dependent variable AI_RISK, there is a moderate positive correlation with TASK_STD (r=0.325) , TIME_PRES (r=0.261), AI_USE (r=0.235) and AI_COMP (r=0.295), suggesting that the higher levels of task standardization, time pressure, Artificial Intelligence usage and Artificial Intelligence competences are associated with an increase in perceived risk of replacement. In contrast, EMP_NEG has a relatively string negative correlation with AI_RISK (r=-0.462) indicating that activities characterized by empathy and negotiation appear significantly reduce AI's perceived risk of replacement. On the other hand, correlations with ERR_CONS and PRIV_REQ are weak or moderate and negative, suggesting a less direct role of these dimensions on perceived risk.

Overall, the correlations are below the critical threshold of multicollinearity ($|r| < 0.8$), while showing some high associations between independent variables between EMP_NEG and TASK_NOV, $r = 0.729$, which justify the use of multivariate models to isolate net effects. These preliminary results support the idea that the perceived risk of AI-driven job substitution is more related to the standardizable and technologically exposed nature of activities, while it decreases in the presence of tasks with a high relational and human content.

Table 3. Correlation Matrix

.	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. AI_RISK	1.00								
2. TASK_STD	0.325	1.00							
3. EMP_NEG	-0.462	-0.534	1.00						
4. ERR_CONS	-0.058	0.247	0.187	1.00					
5. TIME_PRES	0.261	0.027	0.195	0.305	1.00				
6. PRIV_REQ	-0.195	0.265	0.077	0.498	-0.053	1.00			
7. TASK_NOV	-0.233	-0.609	0.729	0.038	0.226	-0.126	1.00		
8. AI_USE	0.235	-0.268	0.222	-0.265	0.073	-0.395	0.24	1.00	
9. AI_COMP	0.295	-0.175	0.294	0.057	0.206	-0.159	0.44	0.453	1.00

4.2. Regression Analyses

In this section, the results of the mains regression models will be presented and discussed in the sequence outlined in section 3.3.

For the goodness of fit of the models, two indicators are used: the R-squared and the adjusted R-squared. The adjusted versions of the indicators were chosen given the incremental nature of the models, these versions increase only if the added variables improve the model beyond what would be expected by chance, making it a more reliable indicator when comparing models of different complexity. Using adjusted R-squared in this study is a more appropriate approach considering that the independent variables are firstly analysed alone and subsequently together with controls, making the comparison between models with different number of variables more reliable. The transition to the full model brings a significant increase in explanatory capacity. This supports the choice to include psychometric and organizational constructs and not limit itself to socio-demographic variables alone.

4.2.1. Model M1 (Base)

Model M1 (Base). Table 4 presents the results of the first model which tests the standalone effect of the independent variable *TASK_STD* on the dependent variable *AI_RISK*. In particular, it evaluates the first hypothesis in a specification that includes socio-demographic controls such age, gender, and experience, while accounting for clustered standard errors.

As hypothesized, the coefficient is positive and statistically significant ($\beta = 0{,}234\,, SE = 0{,}061$). This result seems to confirm the first hypothesis, which posits that tasks characterized by standardized or standardizable activities are associated to a greater risk of replacement by Artificial intelligence perceived by the professional service firm's employees. This finding aligns with prior literature emphasizing the higher grade of standardization typically granted to activities replicable by AI technologies. The results provide positive evidence in favour of Hypothesis 1.

In terms of the model fit, the results indicate that the model explains approximately 17.1% of the variability observed in the replacement risk perceived. Concerning the social-organizational context, the R-squared is coherent with the models which explain perceptions and attitudes, that for their nature are influenced by multiple non observed factors.

The adjusted R-squared estimated at 12.8% is penalized adding regressions and shows the variability quote keeping into account the complexity of the model. The fact that the R-square is greater than the Adjusted R square is totally in line with the statistical theory.

The value of the coefficient suggests that, on average, individuals whose tasks are one unit higher in task standardization report a perceived risk of AI-driven job substitution that is 0.234 points higher on the AI_RISK scale, holding all other covariates constant, providing strong support on the Hypothesis 1

Table 4	Base (M1)			
		Num.Obs.	R2	R2 Adj.
(Intercept)	2.944***	123	0.171	0.128
	(0.546)			
Age	-0.047**			
	(0.017)			
il_tuo_sessoPreferisco non rispondere	0.205			
	(0.137)			
il_tuo_sessoUomo	0.101			
	(0.144)			
anni_di_esperienza_nel_suo_attuale_ruolo_in_azienda6-10	0.232			
	(0.172)			
anni_di_esperienza_nel_suo_attuale_ruolo_in_azienda oltre 10	0.528+			
	(0.287)			
TASK_STD	0.234***			
	(0.061)			

$p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.2. Models M2 (Full)

Model M2 (Full). Table 5 reports the results of the full model specification, in which the independent variables (AI_RISK) is tested along with the complete set of variables. This model serves as the core analytical specification, aiming to represent the combined effect of the predictors related to single activities characteristics in daily employee's tasks and to the perceived risk of replacement by Artificial Intelligence, taking into account the possible alternative explanations through sociodemographic controls. In the following model over the sociodemographic controls, all the variables previously presented are included; TASK_STD, EMP_NEG, ERR_CONS, TIME_PRES, PRIV_REQ, TASK_NOV, and the two control variables; AI_USE, AI_COMP.

The coefficient of EMP_NEG, as hypothesized, remains positive and statistically significant ($\beta = -0.581\,, SE = 0{,}173$), possibly confirming that daily activities that require greater empathy and negotiation with the customer contributes negatively to the risk of replacement perceived by professional service firm's employees, even when more factors are taken into consideration. The results provide positive evidence in favour of Hypothesis 2.

The independent variable TIME_PRES, represents the strict and not negotiable deadline to deliver the task completed, is positive and highly significant ($\beta = 0.330\,, SE = 0.089$), stating that when the employees is running out of time to complete the task the use of technologies based on Artificial Intelligence represents a valid alternative to save time on less relevant activities, prioritizing the delivery of the completed, having a positive effect on the perceived risk of AI-driven job substitution. Ultimately, the results provide positive evidence in favour of Hypothesis 4.

On the other hand, TASK_STD, which has been highly significant in the precedent model (M1) and shown to be a strong contributor to on the perceived risk of AI-driven job substitution, loses significance ($p > 0{,}1$) in the complete model likely due to shared variance with other variables. The other variables added to model absorb part of the variance in the dependent variable which was before attributed to TASK_STD, reducing its contribution and statistical power. As final interpretation, in the stan alone model, TASK_STD could act as a proxy for on the perceived risk of AI-driven job substitution, but in the full model the variable has been separated in several specific variables, consequentially, the individual signal results less observable.

In terms of the model fit, the results indicate that the model explains approximately 56.4 % of the variability observed in the perceived risk of AI-driven job substitution. It is a relevant value concerning the perceptive nature of the phenomenon, and it shows that the introduced constructs add a relevant informative contribution to the literature.

The adjusted R-squared estimated at 51.2% confirms that the increase in explanatory power is not simply driven by adding more variables, but that the additional set of predictors genuinely improves the fit and overall quality of the simpler model.

Compared with M1, M2 shows a much larger increase in explanatory power. This suggests that socio-demographic variables and task standardization alone account for only a limited portion of the phenomenon, whereas the full model captures substantial determinants related to the nature of work and individual's interaction with AI.

In terms of controls variables, AI_USE and AI_COMP are included as controls to take into account the different exposure grade and individual familiarity with Artificial Intelligence and to isolate the effects on the variables part of the analysis. Although not being at the center of the hypotheses both are positively associated with the perceived risk of substitution, suggesting that to a great competencies and interaction with Artificial Intelligence tools correspond perceived risk of AI-driven job substitution

The coefficient of AI_COMP is a positive and strong predictor of the perceived risk of AI-driven job substitution, it is capable to capture individual differences in skills and technical familiarity with AI, which can influence the perception of replacement risk and be correlated with other job characteristics or the adoption of AI tools. The results show interesting insights, employees with greater competences in Artificial Intelligence technologies tend to perceive more clearly their capabilities and therefore to evaluate the possibility of being substituted in their activities.

In the full model, AI_USE was included as a control variable to account for individual differences in the degree of exposure to and operational use of AI, which could directly influence perceived substitutability and, at the same time, be correlated with job characteristics. The results show that AI_USE is positively associated with perceived risk of substitution. Although treated as a control, this evidence suggests that greater direct interaction with AI can increase awareness of its automation capabilities and, consequently, strengthen the perception that certain tasks may be substitutable.

Lastly, in the full model the coefficient ERR_CONS, PRIV_REQ and TASK_NOV don't show a statistically significant association with the perceived risk of AI-driven job substitution, once controlled by other predictors. ER_CONS presents a negative coefficient close to zero ($\beta = -0.053$), PRIV_REQ substantially is null ($\beta = 0.008$) and TASK_NOV is positive but without a statistical significance ($\beta = 0.030$). Overall, these results suggest that suck as dimensions couldn't directly shape the perceived risk, or that their effect has been absorbed, in the current model, by variables more proximal to the mechanism underlying perceived risk. In particular, error consequences and the privacy requirements could influence attitudes towards trust in AI, willingness to adopt AI tools, or perceptions of operational and ethical risk rather than substitution risk; similarly, task novelty and ambiguity could manifest impact only in specific roles or could partially overlap with other job dimensions already included in the model. To conclude these effects may be heterogeneous or non-linear, and thus not fully captured by an average linear specification, which points to potential avenues for future research. The results provide negative evidence in favour of Hypothesis 3,5,6.

Table 5	Full (M2)			
		Num.Obs.	R2	R2 Adj.
(Intercept)	2.273*	123	0.564	0.512
	-1.014			
Age	-0.028+			
	(0.016)			
il_tuo_sessoPreferisco non rispondere	0.004			
	(0.115)			
il_tuo_sessoUomo	-0.054			
	(0.097)			
anni_di_esperienza_nel_suo_attuale_ruolo_in_azienda6-10	0.233			
	(0.176)			
anni_di_esperienza_nel_suo_attuale_ruolo_in_azienda oltre 10	0.450+			
	(0.256)			
TASK_STD	0.100			
	(0.081)			
EMP_NEG	-0.581**			
	(0.173)			
ERR_CONS	-0.053			
	(0.126)			
TIME_PRES	0.330***			
	(0.089)			
PRIV_REQ	0.008			
	(0.090)			
TASK_NOV	0.030			
	(0.112)			
AI_USE	0.271*			
	(0.117)			
AI_COMP	0.481**			
	(0.159)			

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.3. Robustness and Additional Analysis

To ensure the reliability and internal validity of the estimated coefficients, a comprehensive set of robustness checks was conducted. First, for each observation, hat values have been calculated which measure how much an observation is "extreme" among the regressors, and the Cook's distance, which summarizes the overall influence of an observation on the estimates by combining residual size and leverage. In the context of regression, this test is often applied to residuals to validate the normality assumption, which supports the validity of confidence intervals and hypothesis tests derived from OLS estimates.

An alternative model has been estimated removing the influence observations, identified through Influential diagnostics

In Table 5. the robustness analysis shows that the results strengthen after the remotion of influent observations: the principal coefficients maintain a coherent value and, in multiple cases, increase in significance, indicating that the conclusion don't depend on some "atypical" interviewers. It important to highlight, EMP_NEG confirms a negative effect and becoming more intense in the sample without influent observations, suggesting that the relational component of work represents a robust protective factor with respect to the perceived risk of replacement by AI. Similarly, TIEM_PRES remains the positive driver who is more stable and stronger, and according to which the strict deadline for deliverables is associated with a greater perception of job-substitution. Also, variables of exposure and familiar with AI, manage as controls, results robust, AI_COMP increase and become more statistically significant, while AI_USE remains positive and significant with a contained reduction. On the other side, TASK_STD remains not statistically significant and switches its sign without acquiring statistical significance, coherent with the result that the standardization of the task loses its independent effects once considered with other more specific predictors. Finally ERR_CNS, PRIV_REQ and TASK_STD remain not significant in both models, stating the, at least, as direct linear effects on the sample analysed, they don't explain AI_RISK in presence of other drivers which operate through alternative mechanisms.

To assess the multicollinearity presence among the selected variables in the M2 (Full), the Variance Inflation Factors (VIF) has been run. VIF measures how much the variance of an estimated coefficient could result influenced by the correlation with the other regressors.

The results show that the VIFs are contained overall and do not highlight any issues that would compromise inference. In particular, the major VIF is 4,63, followed by 4,45 concerning the Age. Suck values fall within the range commonly interpreted as moderate and they are coherent with the natural relationship among seniority indicators; it expected that the age and the years of experience

could be partially overlapping from an informational point of view. The other regressors have lower VIFs (about 1.27–3.14), indicating a low or moderate linear correlation with the other predictors.

A VIF value above a certain threshold (typically 5 or 10) suggests a problematic level of collinearity, potentially undermining the reliability of the estimated coefficients.

No variables exceeded the commonly accepted threshold of 5, confirming the absence of problematic collinearity in the final model specification (table 6) which would have complicated the estimation of individual regression coefficients, inflated standard errors, and reduced statistical power.

Table 6. VIF values -Multicollinearity study

Variable	*VIF*
Experience: >10	*4,627*
Age	*4,446*
TASK_NOV	*3,140*
EMP_NEG	*2,903*
Experience: 6–10	*2,307*
TASK_STD	*2,169*
ERR_CONS	*1,820*
PRIV_REQ	*1,726*
AI_USE	*1,677*
AI_COMP	*1,602*
Gender: male	*1,371*
TIME_PRES	*1,335*
Gender: prefer not to say	*1,266*

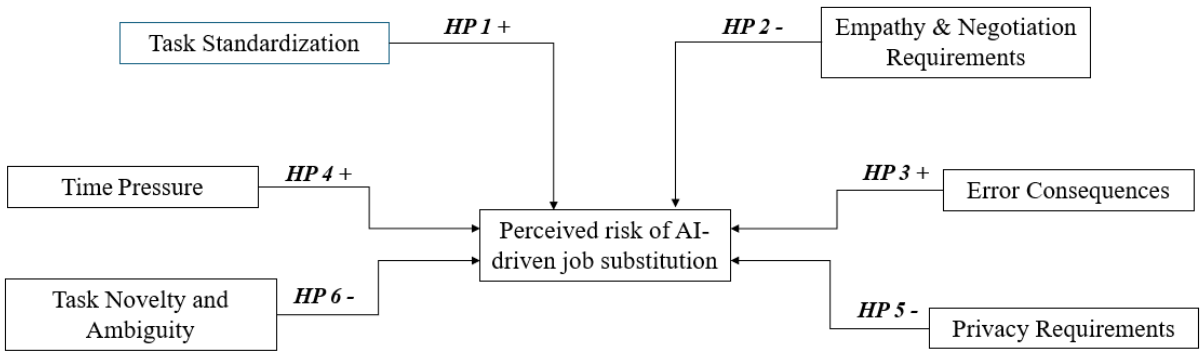
Table 5. Robustness Checks

	Full (M2)	*Full (M2) without influncers*
(Intercept)	*2.273**	*3.285****
	-1.014	*(0.884)*
eta	*-0.028+*	*-0.033***
	(0.016)	*(0.013)*
il_tuo_sessoPreferisco non rispondere	*0.004*	*-0.053*
	(0.115)	*(0.082)*
il_tuo_sessoUomo	*-0.054*	*-0.112*
	(0.097)	*(0.086)*
*anni_di_esperienza_nel_suo_attuale_ruolo_in_*	*0.233*	*0.364***
	(0.176)	*(0.127)*
*anni_di_esperienza_nel_suo_attuale_ruolo_in_*	*0.450+*	*0.621***
	(0.256)	*(0.220)*
TASK_STD	*0.100*	*-0.079*
	(0.081)	*(0.064)*
EMP_NEG	*-0.581***	*-0.716****
	(0.173)	*(0.103)*
ERR_CONS	*-0.053*	*-0.030*
	(0.126)	*(0.089)*
TIME_PRES	*0.330****	*0.533****
	(0.089)	*(0.066)*
PRIV_REQ	*0.008*	*-0.044*
	(0.090)	*(0.067)*
TASK_NOV	*0.030*	*-0.085*
	(0.112)	*(0.091)*
AI_USE	*0.271**	*0.227**
	(0.117)	*(0.090)*
AI_COMP	*0.481***	*0.608****
	(0.159)	*(0.119)*
Num.Obs.	*123*	*105*
R2	*0.564*	*0.737*
R2 Adj.	*0.512*	*0.699*

· *p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001*

In conclusion, the research model presented in the previous chapters is reported, highlighting the results of the hypotheses subjected to empirical verification. The analysis made it possible to distinguish among the theoretically formulated relationships and those actually supported by the data, highlighting which determinants of the content of the work are significantly associated with the perceived risk of substitution by artificial intelligence. The reference to the model therefore makes it possible to systematically summarize the results obtained, clarifying which hypotheses are confirmed, which are partially supported and which do not emerge as statistically significant in the sample analysed.

Fig. 2 – Research Model



HP1 – Task Standardization: the hypothesis finds no support in the full model. Although task standardization shows a positive effect in the base model, this relationship loses significance once the additional explanatory variables are introduced, suggesting that the effect is absorbed by more specific dimensions of the work content.

HP2 – Empathy and Negotiation Requirements: the hypothesis is confirmed. The variable has a negative and statistically significant coefficient ($p < 0.01$), indicating that a greater relational component of work is associated with a reduction in the perceived risk of AI substitution.

HP3 – Error Consequences: Hypothesis is not supported. The estimated coefficient is not statistically significant, suggesting that, in the sample analysed, the significance of the consequences of the error does not exert a direct effect on the perceived risk.

HP4 – Time Pressure: the hypothesis is fully confirmed. Time pressure shows a positive and highly significant effect ($p < 0.001$), indicating that urgent operating environments and tight time constraints are associated with an increase in the perceived risk of substitutability.

HP5 – Privacy Requirements: the hypothesis finds no empirical evidence. The variable is not statistically significant, suggesting that privacy requirements do not directly affect the perception of substitutability in the estimated model.

HP6 – Task Novelty and Ambiguity: The hypothesis is not supported in the full model. Although theoretically associated with lower substitutability, the relationship does not emerge as statistically significant when controlled for the other dimensions of work.

Overall, the results indicate that the most relevant dimensions in determining the perceived risk of substitution are time pressure and the relational skills required by the task, while other characteristics of the job do not show a statistically significant independent impact in the final model.

4.3. Discussion

In the light of the literature examined, the empirical results suggest that the perception of substitutability is not primarily anchored to static individual characteristics, such as age, gender or seniority, but to the concrete configuration of work and the ways in which artificial intelligence is integrated into operational processes. the most recent studies on the adoption of GenAI in professional contexts show that the impact of technology emerges from the interaction between humans and systems in concrete operational flows, and not from isolated individual attributes. Thus, the perception of substitutability appears as a situated and as aorganizational phenomenon, rooted in the nature of activities and the design of processes, rather than in structural personal characteristics.

First of all, the robust and positive effect of the time pressure results fully coherent with the state of art which highlights as strict limits deadlines and elevated workload conditions foster a greater attribution to automated support systems. In contexts characterized by urgencies and attentive limited resources, the individual tends indeed to delegate easier the phases of decision-making process to the technologies, reducing the propensity for critical verification and active control of outputs. This mechanism is largely discussed within the studies on the automation bias and the usage of the decision support systems (Goddard et al.,2012; Rieger & Manzey, 2024), it contribute to make more interesting the idea that Artificial Intelligence could substitute, at least partially, the human intervention. Moreover, the results on the cooperation between human and machine show

that the time management concerning the different phases of the task influence significantly the integration grade of the algorithmic recommendations (Cao et al., 2023), strengthening the interpretation that time pressure not only increases the use of Artificial Intelligence, but also amplifies its perception of potential substitutability.

Secondly, the negative and stable effect of relational components, measured through empathy and negotiation, is consistent with the extensive literature that identifies social skills as one of the main "bottlenecks" in automation processes. Activities that require interpersonal interaction, context lecture, implicit signals interpretation and building trust with other individuals difficultly can be integrally codificated in explicit rules or replicated through standardized algorithmic logic. In this prospective, Frey and Osborne (2017) place social skills among the factors that reduce the likelihood of computerization of occupations, while Deming (2017) highlights how social skills assume an increasing value in advance job position present in the market precisely because they are complementary to digital technologies. Similarly, the OECD (2023) points out that transversal skills such as collaboration, persuasion and coordination are less "mappable" in structured input-outputs, making such activities more resilient in front of technologies innovation. The empirical results of the thesis are therefore part of this trend, showing that, as the relational content of the work increases, the perception of risk of substitutability by Artificial Intelligence decreases.

Finally, the fact that task standardization is significant in the basic model but loses significance in the complete model is consistent with the interpretation according to which routine and codability are general indicators of technological substitutability, but do not exhaust its determinants when considering more specific dimensions of the work content. The literature has amply shown that standardized and repetitive tasks are more exposed to computerization (Autor et al.,2003; Brynjolfsson et al.,2018), however, the results suggest that the individual perception of risk is explained more precisely by concrete operational factors, such as the relational component of tasks or urgent organizational conditions, as well as by the degree of direct interaction with AI. At the same time, the absence of significant direct effects for variables such as privacy requirements and the consequences of error does not imply their theoretical irrelevance, but indicates that these dimensions could influence different outcomes, such as the propensity to adopt or the level of trust in technologies or operate in a conditional and non-linear way. This is consistent with studies on privacy concerns and trust in algorithms, which highlight how perceptions of risk and technological acceptance depend on complex and contextual behavioural mechanisms (Malhotra et al.,2004; Acquisti et al.,2015; Dietvorst et al.,2015; Hughes et al.,2025).

Such evidence therefore opens up space for future analyses based on specifications with interaction effects, thresholds or nonlinear models, in order to grasp more precisely the conditions under which these factors become relevant.

5. Conclusions

This study investigates perceived risk of AI-driven job substitution by professional service firm's employees, with the aim to understand how such perception could be explained through individual characteristics, task composition and factor related to artificial intelligence exposure and familiarity. The empiric analysis of the main hypothesis has been conducted through linear regression models with incremental approach, the model presented were: Base model (M1) with focus on one of the most discussed cause of AI-driven job substitution, the standardization of the task, and socio-demographic controls, and a second complete model (M2) which introduce a larger set of variables and constructs in the artificial intelligence context.

The results highlight first of all that the transition from M1 to M2 involves a clear leap in explanatory capacity: the base model explains a limited quote of the perceived risk variability, while the complete model intercepts substantial determinants related to the job nature and to Artificial intelligence interaction. Such improvement isn't just attributable to the adding variables, but it reflects the information contribution of added predictors, coherently with the idea that the substitution perception doesn't depend just on the individual profiles, but rather from more "operational" dimensions of work activity.

In terms of effects, in the complete model some robust drivers emerge. The time pressure (TIME_PRES) results systematically associated to an increasing perceived risk in contexts in which the task is complete under urgency and tight deadlines, in this case Artificial intelligence can be interpreted as a technology capable to accelerate process and to automate internal activities, making the idea of substitutability more salient. In contrast, the relational component of work, measured by EMP_NEG, is associated with a reduction in perceived risk: when the activities require empathy, negotiation and complete interactions, technology appears less capable to substitute the human component and not sufficiently able to replicate human judgment and communication. Alongside these elements, the variables linked to the Artificial Intelligence dimension, although treated as controls in the model, also show a non-negligible role: great level the artificial intelligence usage (AI_USE) and great level of artificial intelligence competencies (AI_COMP) are connected to a greater perceived risk of AI-driven job substitution. Suggesting that the direct exposure and technical familiarity can increase the awareness of the capacity of the automation.

An interesting result concerns the task standardization variable (TASK_STD). In M1, it results positively related to the perceived risk, coherently with literature on the routine activities and codifiable. However, in the complete model M2 it loses significance, indicating that the standardization doesn't maintain an independent impact when other specific dimensions of the job

activities and exposure to artificial intelligence factors are introduced. The following variable seems to be a synthetic indicator but, once, disaggregated into more granular constructs, it gives up some of its explanatory power.

Other constructs, like the error consequences (ERR-CONS), privacy and confidentiality requirements (PRIV-REQ) and task ambiguity and novelty (TASK_NOV) don't show statistically significant association in the complete model. The evidences don't imply necessarily that suck dimensions are absolutely irrelevant, but suggests that, in the analysed perimeter and as direct linear effects, they don't explain autonomously the perception of substitution once they are considered as main drivers. It is plausible that they impact different outcomes or that they operate through conditional mechanisms not captured by the baseline specification.

Overall, the result contributes to clarify that the perceived risk of AI-driven job substitution in Professional Service Firm is particular sensitive to two dimensions: organizational conditions which increase the perceptions of automatization and relational contents that make work less substitutable and more distinctive compared to the current capacity of technology. From a decision-making point of view, this suggests that strategies based on artificial intelligence adoption should be accompanied by interventions on job design: to reduce bottlenecks and chronicle urgencies, reshape repeatable activities and to valorize relational components could mitigate the perceived risk of substitution. At the same time, the positive relationship between AI_USE and AI_COMP and perceived risk suggests that AI training and literacy can increase awareness and realism regarding the technology's capabilities: to avoid counterproductive effects on the organizational climate, it is advisable to combine technical training with clear communication about objectives, boundaries of use, and implications for roles and careers.

5.1. Managerial Implications

In the next paragraph will be presented what might be the main managerial implication from a theoretical and practical point of view. First of all, the organization communication and the perception management concern the way how the risk perceive could be managed from the firm. The organization should adopt a clear end structured communicative strategy, capable to lead the internal narrative forward to the concept of complementarity between human and machine, leveraging the support that technologies can give in daily activities, they can help reducing organizational anxiety, foster technology acceptance, and sustain trust during digital transformation processes.

A further managerial implication concerns the time pressure management in organizational contexts. The evidence suggest that Professional Service Firms should undertake interventions on the process design, adopting alternative solutions which reduce the overload structural conditions and favour of a balanced technology integration into the process. Artificial Intelligence should be interested within well-defined workflows, with explicit roles and responsibilities in the way to configure if-self as an operative and decisional support instrument, promoting sustainable models of human-AI collaboration.

An additional managerial implication could be represented by the necessity of the job design in a prospection oriented to the complementarity of human competences and technological competences. This suggests that organizations should design and restructure tasks in a way that enhances these components, fostering the assignment of more standardisable and repetitive tasks to technologies, and preserving for human input those functions that require contextual judgment, social understanding, and mediation.

5.2. Limitations and Future Research Directions

Despite the contributions offered by this study, it is important to highlight certain limitation which, in this context, should be taken into consideration in order to accurately define the true scope of the findings and to suggest possible direction for future research. Firstly, despite the number of interviews was adequate to estimate the proposed models and to find statistically significant relationships between variables, the number remains relatively small compared to the variety of roles and work contexts potentially affected by the adoption of Artificial Intelligence. Consequently, the evidence obtained should be interpreted as indicative and contextualized to the empirical perimeter of the study, avoiding generalized inferences at the macro level without further verification.

Secondly, additional limitations may concern the potential risk of endogeneity and omitted variables bias. Despite the models include different control variables is not possible to surely exclude that some relevant not observed variables influents simultaneously both predictor and dependent variables, like strategic exposition to innovate, organizational culture or business climate related to the technology. Future research could address this limitation through longitudinal designs, instrumental variable tools, more granular fixed-effects models, or quasi-experimental approaches, in order to strengthen the causal interpretation of observed relationships.

Lastly, the empirical analysis is based on linear regressions that assume a linear and additive relationship between the independent variables and the perceived risk of substitution by AI. However, it is plausible that some relationships are non-linear or conditional in nature, may intensify only beyond certain thresholds, or vary as a function of interaction with other variables. As a result, the model may not fully capture the complexity of the underlying relationships. Future research could explore models with quadratic terms, interactions between variables, nonlinear specifications or more flexible, in order to verify the robustness of the results and investigate the nature of the observed relationships.

To conclude this chapter, while this study provides a significant contribution to the deeper understanding of how the employees perceive the risk the new innovative technologies could replace them in their daily activities, it also highlights new avenues for future researchers. The observed correlation effects, the influence of control variables, and the variability among employees underscore the complexity of the innovative and implementation process within the firm. Therefore, a broader and more comprehensive research agenda will be essential to fully capture the evolving relations between human and machine in the contemporary transformations.

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