PASF Mapping and Agentification Risk Across 250 Office and Knowledge-Work Roles in the Netherlands and European Context

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Abstract

This paper presents an expanded empirical operationalization of the **PASF framework** for analysing office and knowledge work through task distributions rather than occupation-level labels. Building on an earlier proof-of-method pilot, the study extends the scope to **250 Netherlands/EU office roles** distributed across ten role families and mapped through a repeatable pipeline using occupational normalization, public taxonomies, task decomposition, rubric-based PASF coding, and confidence-rated aggregation [1] [2] [3]. The resulting dataset makes it possible not only to estimate role-level distributions across **PASF Zones I-IV**, but also to compare categories, identify structural patterns, and construct a new risk model for large-scale **agentification**. Across the 250-role dataset, the mean distribution is **18.3% in Zone I**, **36.0% in Zone II**, **35.3% in Zone III**, and **10.4% in Zone IV**, with a mean confidence score of **0.851**. Exactly **125 roles** are primarily dominated by Zone II and **99 roles** by Zone III, while no analysed role is predominantly Zone IV [4]. The distribution therefore suggests that office-work transformation is concentrated in the middle of the PASF spectrum, where structured workflows and contextual interpretation coexist. A new **Agentification Risk Score (ARS)** is introduced to estimate which jobs are most susceptible to substantial delegation to AI agents. Rather than equating risk with routine alone, the model combines execution exposure, workflow-reasoning synergy, digital cognition leverage, task concentration, decomposition readiness, and a strategic-responsibility penalty. The highest-risk roles are concentrated in coordination-heavy, documentation-rich, and reasoning-dependent office work rather than in purely repetitive work [5].

Keywords: PASF, agentification, task-based analysis, occupational mapping, future of work, generative AI, O*NET, ESCO, job redesign

1. Introduction

Generative AI has made it increasingly difficult to discuss the future of work using coarse occupational labels alone. The growing capability of AI systems to coordinate tools, manage workflows, process language, and act across bounded tasks means that job transformation increasingly depends on the **structure of tasks within roles**, not merely on job titles [6] [7] [8]. This is especially true for office and knowledge work, where much of the relevant activity is digitally mediated and already partially formalized.

The PASF framework is useful in this context because it models work as a **distribution across four zones**. In the formulation used here, **Zone I** captures highly structured and repetitive activity, **Zone II** captures bounded workflow execution and semi-structured coordination, **Zone III** captures contextual analysis and interpretation, and **Zone IV** captures strategic, normative, and end-responsibility work. PASF is therefore not a binary automation scale but a structural representation of occupational composition [1] [2].

Earlier work in this project demonstrated that PASF could be translated into a pilot research pipeline for ten roles. The present paper extends that effort in three ways. First, it scales the empirical base from a ten-role proof-of-method to a **250-role office-work dataset**. Second, it integrates summary, category, role-level, and full-population visual evidence into a single academic manuscript while relocating the extensive table-only materials to a standalone **Data Appendix**. Third, it develops an explicit **Agentification Risk Score** that ranks all 250 roles by the likelihood that a large share of their activity could be delegated to AI agents under realistic workflow conditions [4] [5].

The paper therefore addresses two linked research questions, reported in the accompanying **Data Appendix, Table D1**. The argument developed below is that **agentification risk** should not be reduced to pure routinization. Jobs become especially susceptible to deep agentic delegation when they combine structured or bounded workflows with enough reasoning content for agents to execute multi-step tasks, while still lacking the strategic accountability that keeps humans decisively in the loop.

2. Background and Related Work

The conceptual foundation of this paper lies in the **task-based view of technological change**. Autor, Levy, and Murnane showed that digital technologies affect the demand for different task types rather than uniformly displacing occupations [6]. Later research on automation and new tasks further demonstrated that technology both substitutes and reconfigures work, implying that occupational labels can obscure the real dynamics of labor transformation [7]. The OECD extended this point by showing that estimated automation risk falls when tasks, rather than occupations, are used as the core unit of analysis [10].

This distinction is directly relevant for AI. Recent research on labor-market impacts of generative AI suggests that exposure is unevenly distributed across job content and often clusters in specific activities such as writing, information handling, and decision support rather than full-job replacement [8]. The ILO similarly cautions that **exposure indicators are not equivalent to realized substitution**, because institutions, governance arrangements, professional responsibility, and redesign choices mediate whether exposure becomes displacement, augmentation, or role transformation [9].

Public occupational infrastructures provide the necessary empirical scaffolding for a PASF implementation. **O*NET** supplies task-rich occupational descriptions, crosswalks, and a stable occupational ontology [11]. **ESCO** adds a European occupation-and-skills layer that is especially relevant for Netherlands and EU alignment [12]. For eventual Dutch localization, **CompetentNL** offers a further semantic infrastructure that can anchor future versions of PASF more directly in local labor-market categories [13]. Even so, none of these systems alone provides a PASF-style estimate of how work is distributed across structured, bounded, interpretive, and strategic layers. That is the methodological gap addressed here.

The present study also departs from conventional automation-risk narratives by focusing on **agentification** rather than automation in the narrow sense. In this paper, agentification refers to the degree to which work can be decomposed, orchestrated, delegated, supervised, and partially executed by AI agents acting across multi-step workflows. Agentification is therefore broader than pure rule automation and narrower than total job displacement. It includes the possibility that a job remains human-led while a large portion of its operative workload becomes agent-executable.

3. Method

3.1 Study Design

The research design combines the earlier pilot logic with a scalable role-mapping workflow for a larger office-work population. Each role was normalized, matched primarily to **ESCO** and secondarily to **O*NET** where helpful, decomposed into representative tasks or task clusters, coded into PASF zones, and aggregated into role-level distributions with a confidence score [2] [3] [4]. The ordered workflow stages are reported in the accompanying **Data Appendix, Table D2**.

3.2 Scope and Sample

The expanded study covers **250 office and knowledge-work roles** across ten equally sized categories: Administration and Operations; Finance and Accounting; Human Resources and Recruitment; Sales and Customer Success; Marketing and Communications; Legal, Compliance and Governance; IT and Digital Workplace; Data Analytics and Research; Project, Program and Product Management; and Public, Education and Health Administration [2] [4]. This scope deliberately excludes primarily physical and craft occupations so that the sample remains analytically focused on work that is text-rich, digitally mediated, process-intensive, or coordination-heavy.

The result is a balanced comparative design in which each category contributes **25 roles**. This makes it possible to compare structural patterns without category-size bias. Mean task count across the dataset is **7.92**, and role confidence averages **0.851**, indicating that the estimates are intended as structured, auditable research assessments rather than direct time-use measurements.

3.3 PASF Coding Logic

The coding rubric follows the earlier pilot but is now applied at scale. **Zone I** is assigned to highly structured and repetitive work. **Zone II** is assigned to bounded workflows involving progression, controlled interaction, exception routing, and process coordination. **Zone III** is assigned to analytical, interpretive, diagnostic, and synthesis-heavy work requiring context. **Zone IV** is reserved for normative, strategic, governance-related, and final-accountability activity [1] [2].

The aggregated score for each role is not a simple task count. It is a structured estimate derived from the reconstructed task mix, informed by the relative importance of activities in the role and then quality-checked for plausibility. For this reason, PASF percentages in this paper should be interpreted as comparative research estimates rather than immutable occupational facts.

3.4 Agentification Risk Model

The new **Agentification Risk Score (ARS)** extends PASF from descriptive mapping to analytical ranking. The objective is to estimate the likelihood that a job can be **substantially agentified**, meaning that a large share of its work can be delegated to AI agents operating across decomposed workflows. The model intentionally does not equate risk with routine alone.

The ARS is built from six components [5]. Their operational meaning and direction are summarized in the accompanying **Data Appendix, Table D3**, while the weighted formula and rationale remain in **Appendix A** of this main paper.

The weighted model produces a continuous score between 0 and 100. High values indicate roles that combine bounded process execution with enough reasoning to support agentic delegation, while low values indicate roles buffered by governance, institutional responsibility, strategic judgment, or heterogeneous role composition. Full data tables are therefore separated from the narrative argument while remaining available in the companion appendix [5].

3.5 Study Positioning

This paper should be read as a **large-scale structured empirical estimate**. It is more than a conceptual proposal because it produces a full dataset, comparative figures, ranked outputs, and a separate evidence appendix. At the same time, it remains short of direct observational validation. The method relies primarily on public occupational descriptions and structured reconstruction, not on enterprise workflow logs, timesheets, or ethnographic observation. This implies that the results are strongest as a comparative analytical instrument and weaker as an exact measure of organization-specific job design.

4. Results: PASF Structure of 250 Office Roles

4.1 Aggregate PASF Distribution

Across the complete 250-role dataset, the average occupational profile is concentrated in the middle of the PASF spectrum. Zone II accounts for **36.0%** of average role content and Zone III for **35.3%**, while Zone I accounts for **18.3%** and Zone IV for **10.4%** [4]. This indicates that the typical office role in the sample is not primarily defined by pure routine, nor by pure strategy, but by a layered combination of bounded process execution and contextual interpretation.

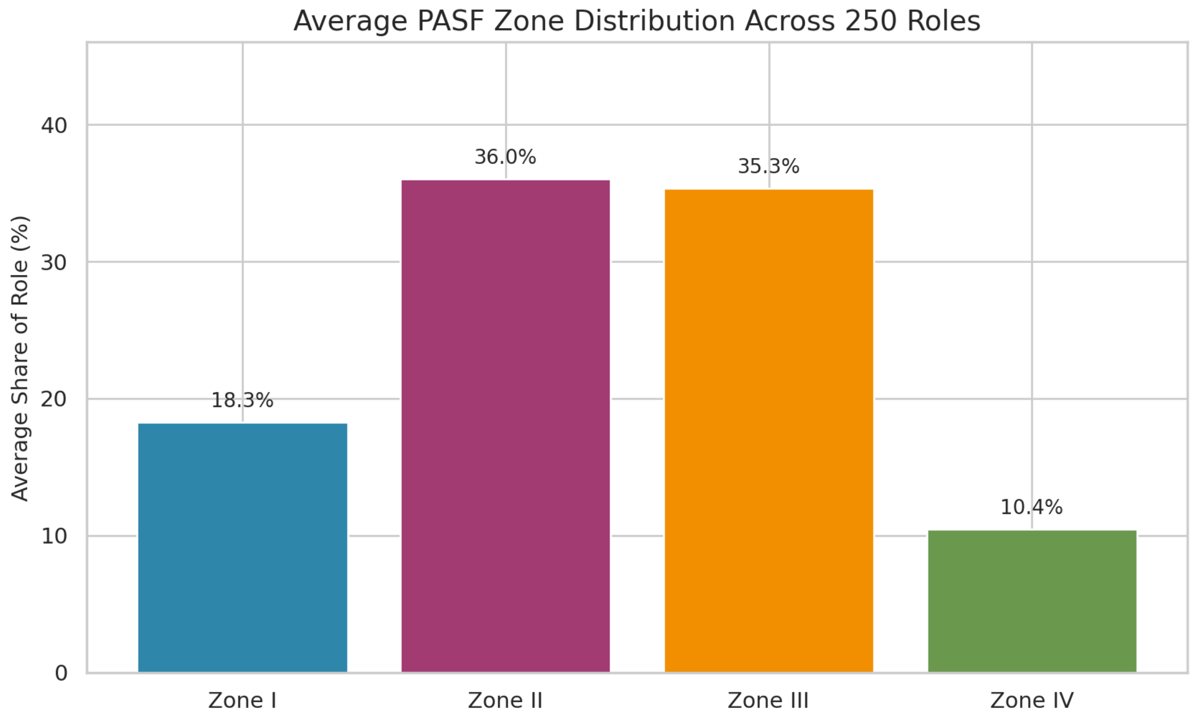

Figure 1

Average PASF zone distribution across the 250-role dataset

The dominant-zone distribution reinforces this pattern. Exactly **125 roles** are dominated by Zone II and **99 roles** by Zone III, while only **26 roles** are dominated by Zone I and **0 roles** by Zone IV [4]. In empirical terms, strategic and normative work appears widely as a component of office roles, but rarely as the sole defining layer.

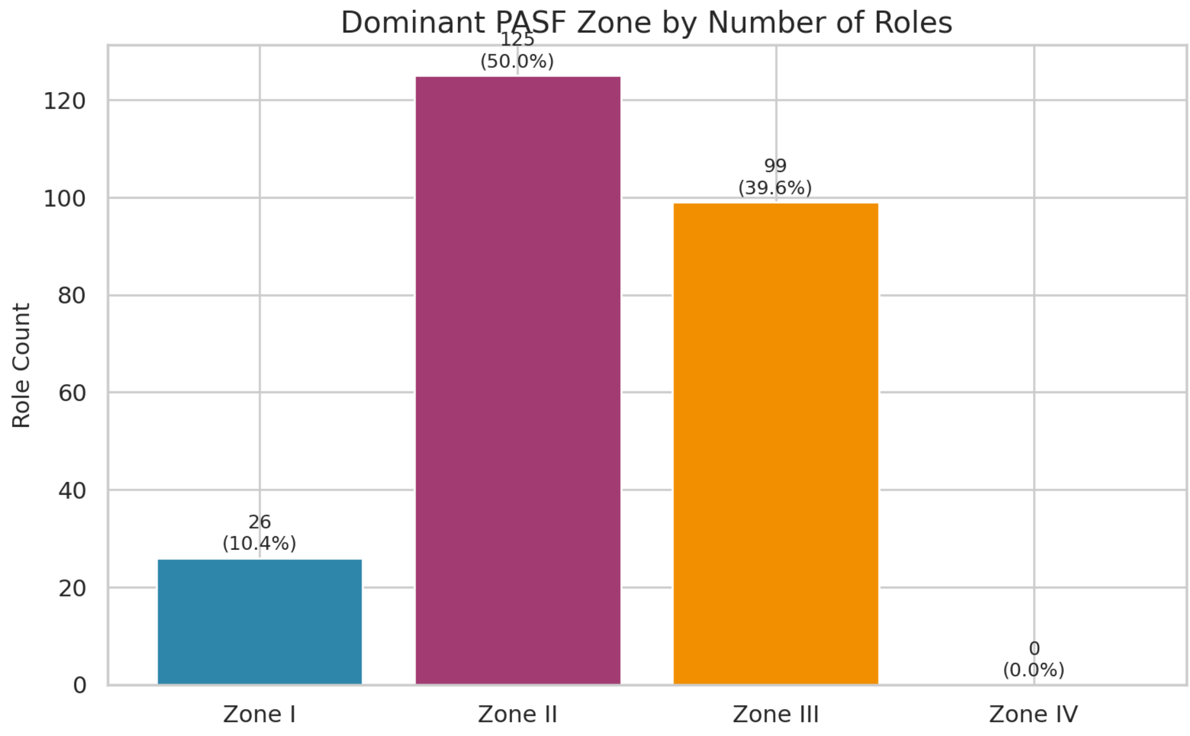

Figure 2

Dominant PASF zone across all analysed roles

4.2 Category-Level Structure

The category comparison reveals a clear pattern of stratification across office-work families. The strongest **Zone III** signatures appear in **Data Analytics and Research**, **Project, Program and Product Management**, **Marketing and Communications**, and **Public, Education and Health Administration**. By contrast, **Administration and Operations** and **Finance and Accounting** retain the highest average Zone I shares, though even these categories remain mixed rather than purely routine [4].

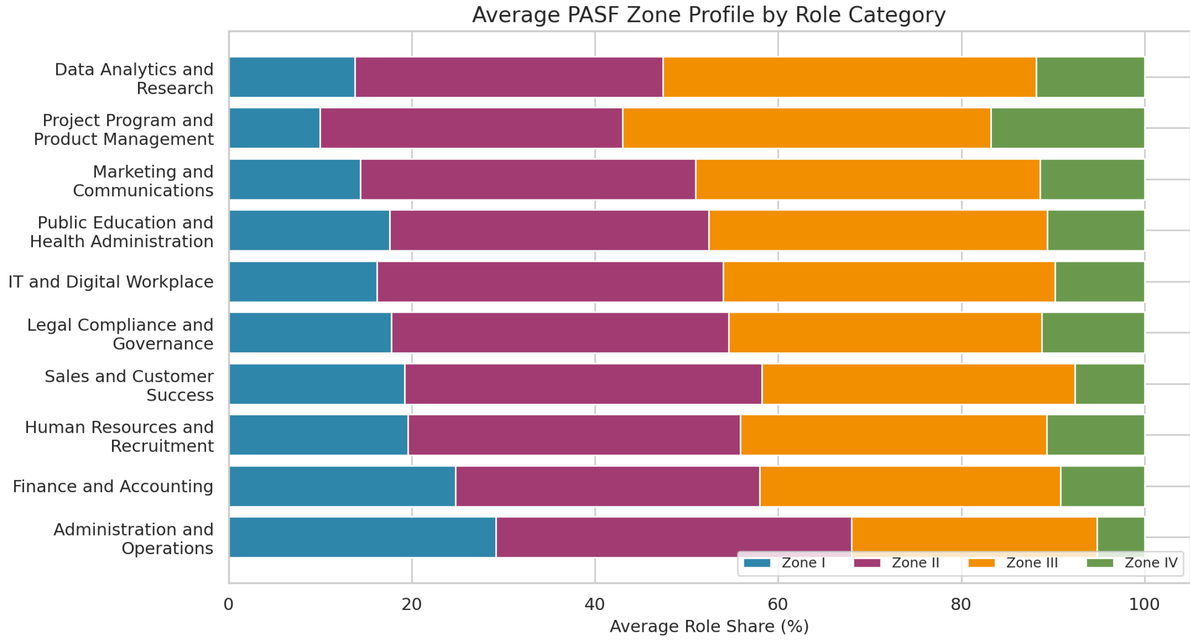

Figure 3

Average PASF zone profile by role category

The full numerical category summary is available in the standalone **Data Appendix, Table D4** so that the main results section remains visually focused while still preserving the complete comparative evidence.

The heatmap makes this comparison easier to read at a glance. The most visible polarity lies between **Administration and Operations**, with the highest average Zone I share, and **Data Analytics and Research**, with the highest average Zone III share. Yet the overall picture remains one of mixed profiles: most categories contain meaningful shares of both bounded workflow work and interpretive work.

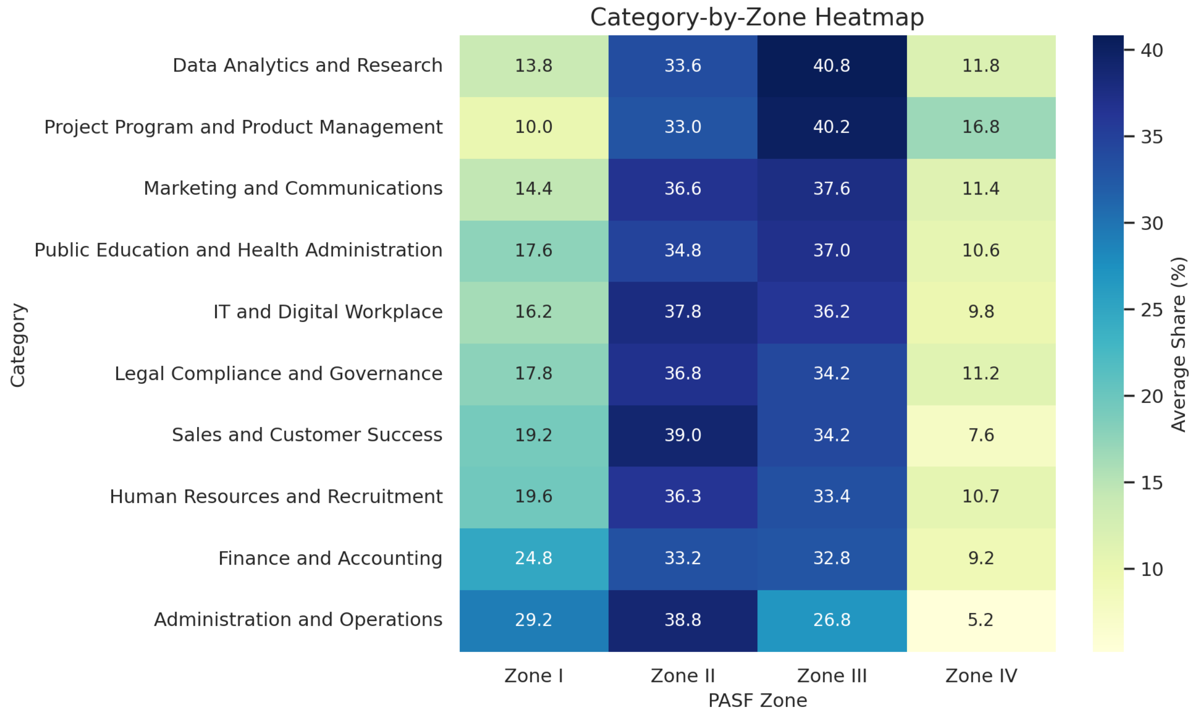

Figure 4

Category-by-zone heatmap

4.3 Role-Level Extremes

At the more structured end of the distribution, the strongest Zone I profiles include **Front Office Coordinator**, **Billing Specialist**, and **Housing Administration Officer**. These roles represent the outer edge of routinized office work in the sample, but even here the jobs are not devoid of semi-structured coordination or exception handling [4].

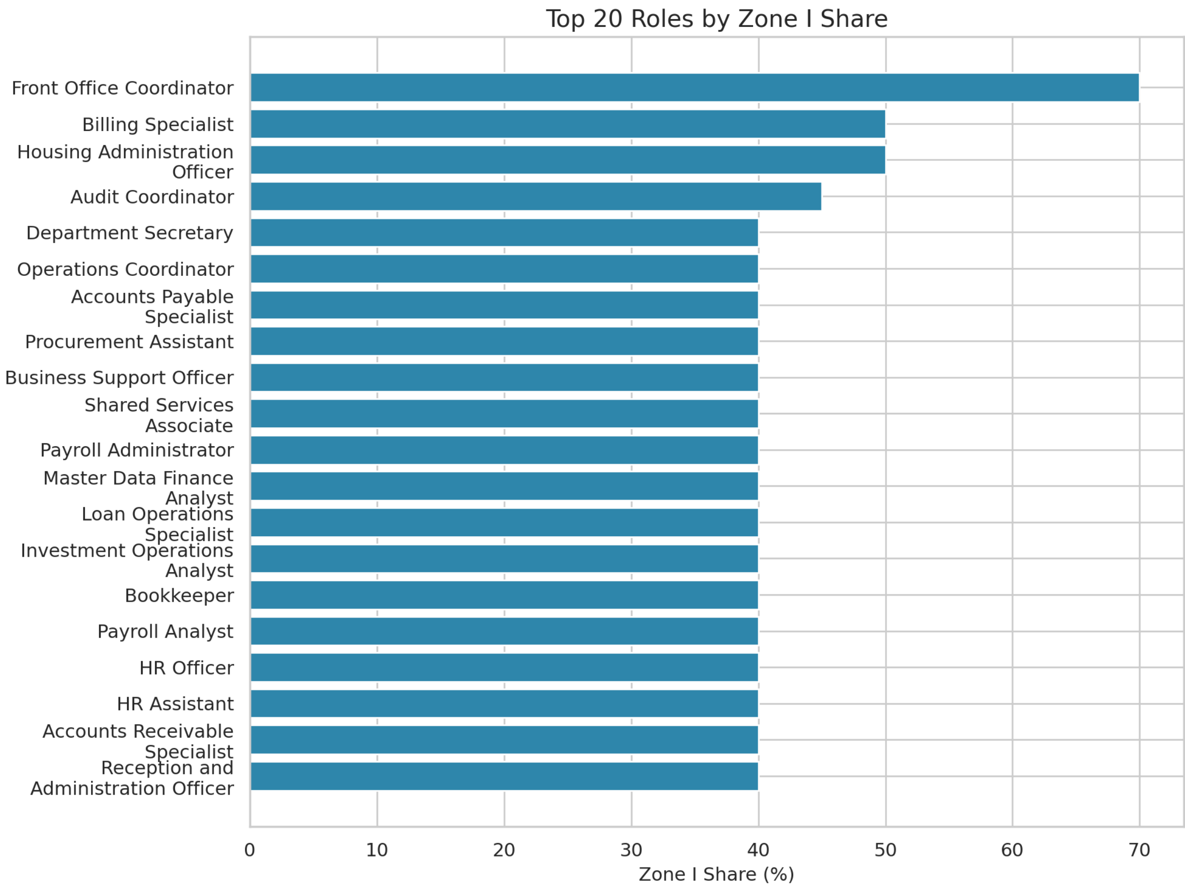

Figure 5

Top 20 roles ranked by Zone I share

At the interpretive end, the strongest Zone III profiles include **Business Systems Analyst**, **Research Analyst**, **Survey Research Coordinator**, and **Operations Research Analyst**. These roles remain embedded in organizational workflows, but their dominant activity is contextual reasoning rather than rule-following alone [4].

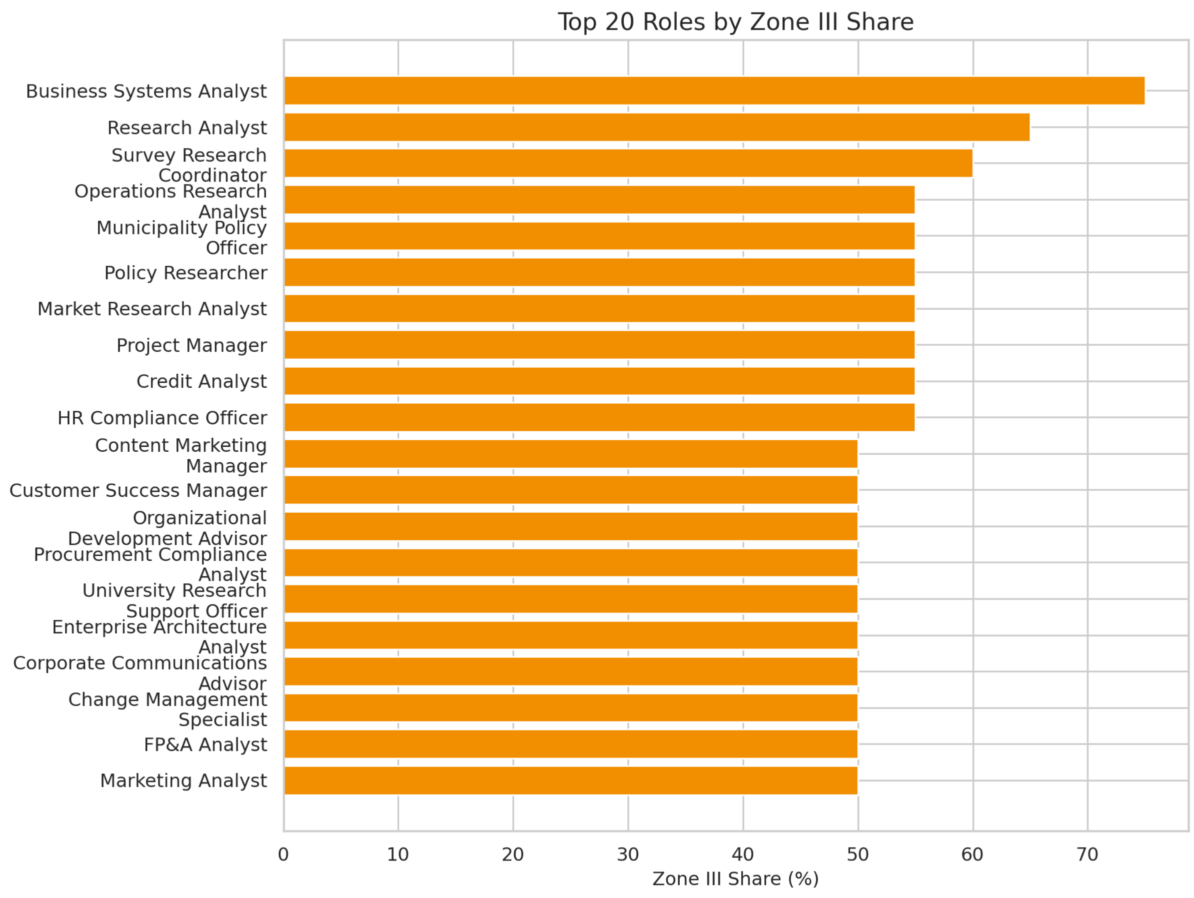

Figure 6

Top 20 roles ranked by Zone III share

The strongest Zone IV shares occur in roles such as **Product Manager**, **Labor Relations Analyst**, **Management Consultant**, and **Program Manager**. Importantly, none of these becomes predominantly Zone IV. Even the most strategic roles in the dataset remain mixed profiles with substantial amounts of Zone II or Zone III work [4].

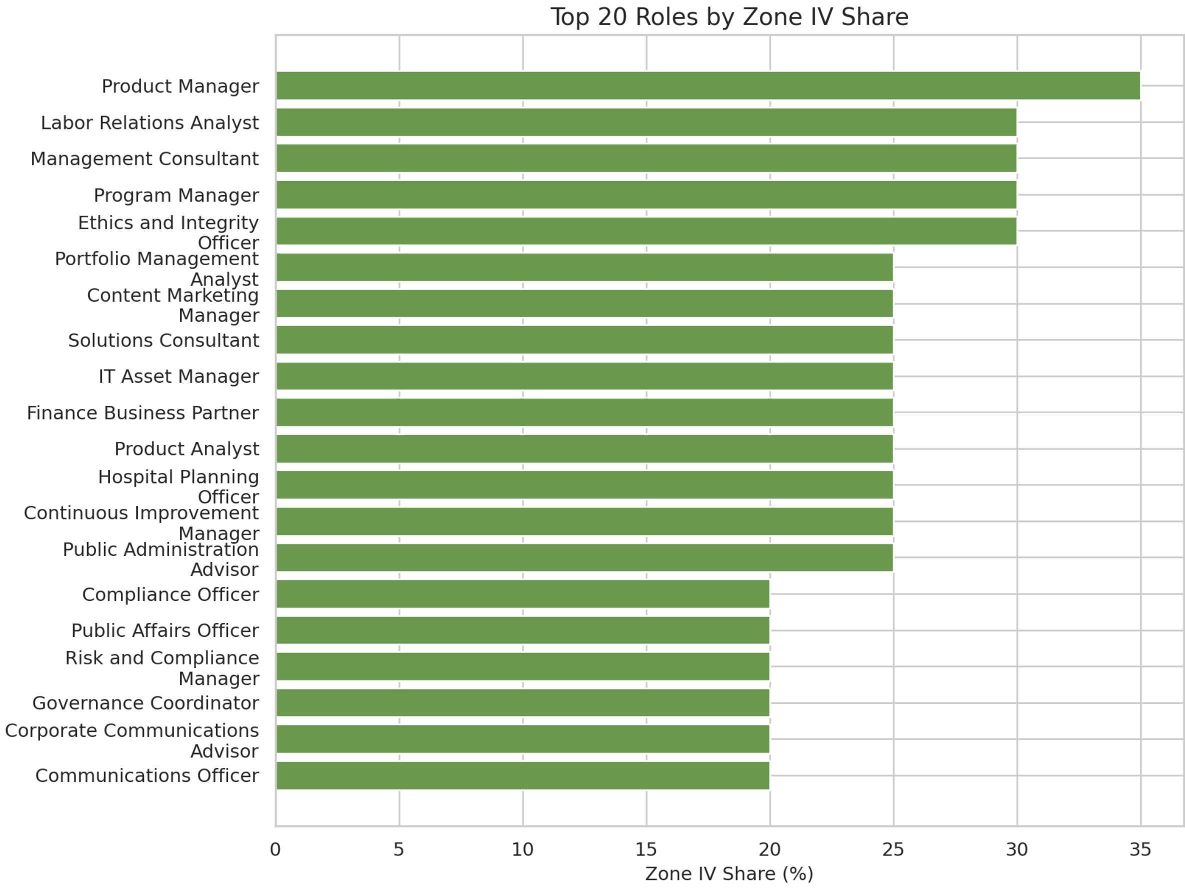

Figure 7

Top 20 roles ranked by Zone IV share

4.4 Distribution, Spread, and Confidence

The broader distribution confirms that Zone II and Zone III dominate the interquartile mass of the dataset. Zone IV is present across many roles but generally remains secondary. Confidence is concentrated in the mid-to-high range, with a mean of **0.851**, supporting the internal plausibility of category-level and role-level comparison while still leaving room for future validation [4].

[Figure 8: Distribution of role-level PASF shares across the full dataset]

[Figure 9: Confidence distribution across the 250-role set]

The scatter between Zone II and Zone III shows that many roles cluster along the boundary where bounded workflow execution and contextual interpretation co-exist. That intermediate zone is analytically important because it represents the part of office work most plausibly reorganized by agentic systems that both follow workflow logic and provide contextual assistance.

[Figure 10: Role positioning between Zone II and Zone III, with confidence encoded in point size]

The balance metric further suggests that more mixed roles are not systematically lower in confidence. This matters because it shows that profile hybridity is not simply a byproduct of indecisive coding, but a substantive property of office work in the dataset.

[Figure 11: Relationship between role balance and confidence]

5. Results: Agentification Risk Across 250 Roles

5.1 Overall Distribution of Risk

The ARS distribution is moderately wide, with a mean of **38.78**, a median of **38.81**, a maximum of **54.88**, and a minimum of **24.42** [5]. This indicates that substantial agentification potential is neither universal nor confined to a tiny elite of roles. Rather, it is distributed across a meaningful band of office occupations.

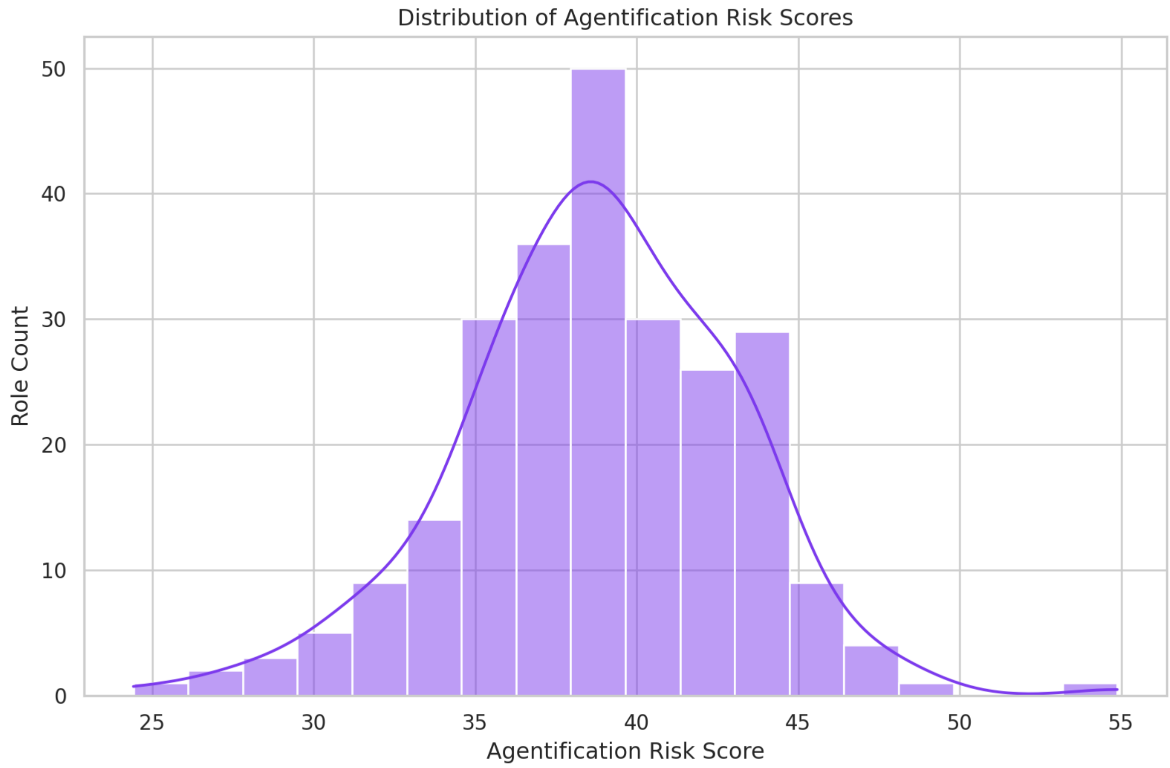

Figure 12

Distribution of agentification risk scores across the 250 roles

5.2 Top-Risk Roles

The ranking visual shows that the highest-risk segment spans multiple domains, including public administration, research coordination, HR, legal compliance, IT administration, and finance. This reinforces the paper’s central claim that the most agentifiable jobs are not simply those with high routine content. Rather, they are jobs in which **process, documentation, case progression, coordination, and intermediate judgment** can be structured into multi-step agentic workflows [5].

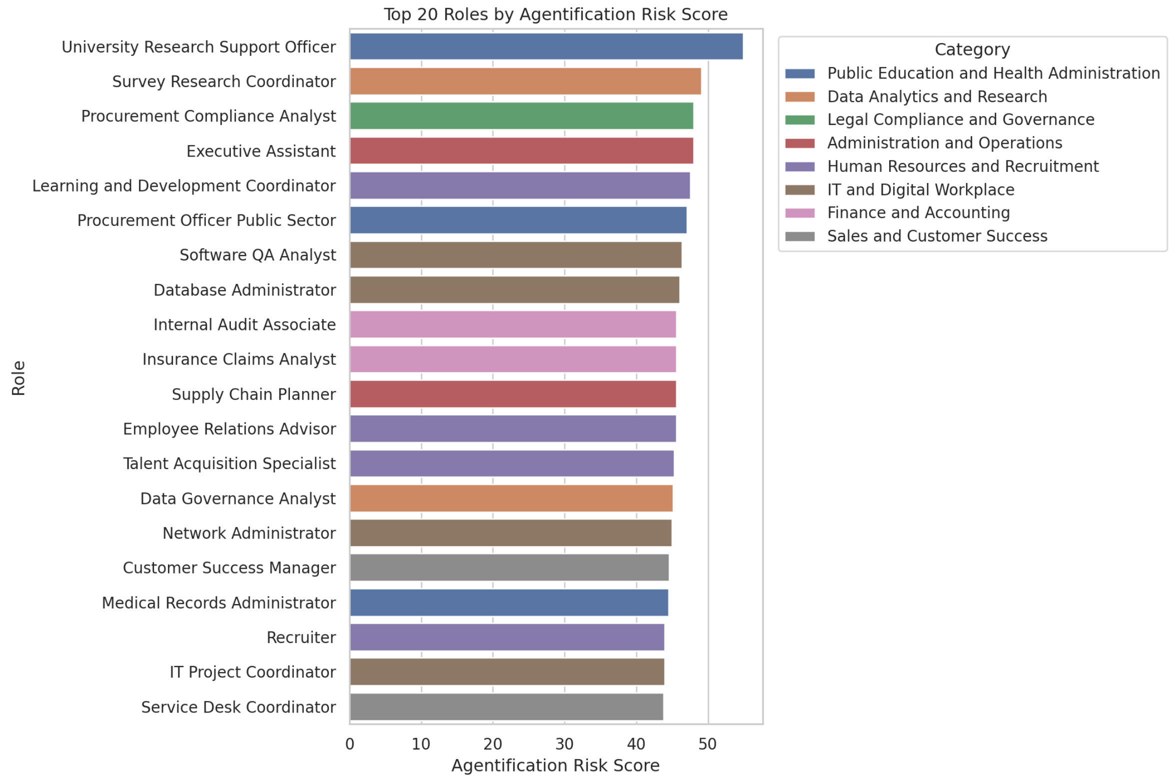

Figure 13

Top 20 roles by Agentification Risk Score

The complete top- and bottom-risk comparison is reported in the standalone **Data Appendix, Tables D6-D7**, allowing the main text to prioritize interpretation over repeated tabular detail.

The presence of roles such as **University Research Support Officer**, **Survey Research Coordinator**, **Procurement Compliance Analyst**, and similar coordination-heavy roles in the high-risk segment illustrates that agentification risk rises when a role is simultaneously document-rich, process-bound, coordination-heavy, and reasoning-dependent. These are precisely the contexts in which a chain of agentic tools can interact with calendars, records, templates, knowledge bases, tickets, and standard operating procedures.

5.3 Category-Level Risk

At category level, the highest mean ARS values appear in **Sales and Customer Success** (**40.18**) and **IT and Digital Workplace** (**39.84**), while the lowest category mean occurs in **Project Program and Product Management** (**36.85**) [5]. The difference across categories is real but moderate, which indicates that agentification potential is not monopolized by one domain. Instead, the phenomenon cuts across most office-work families.

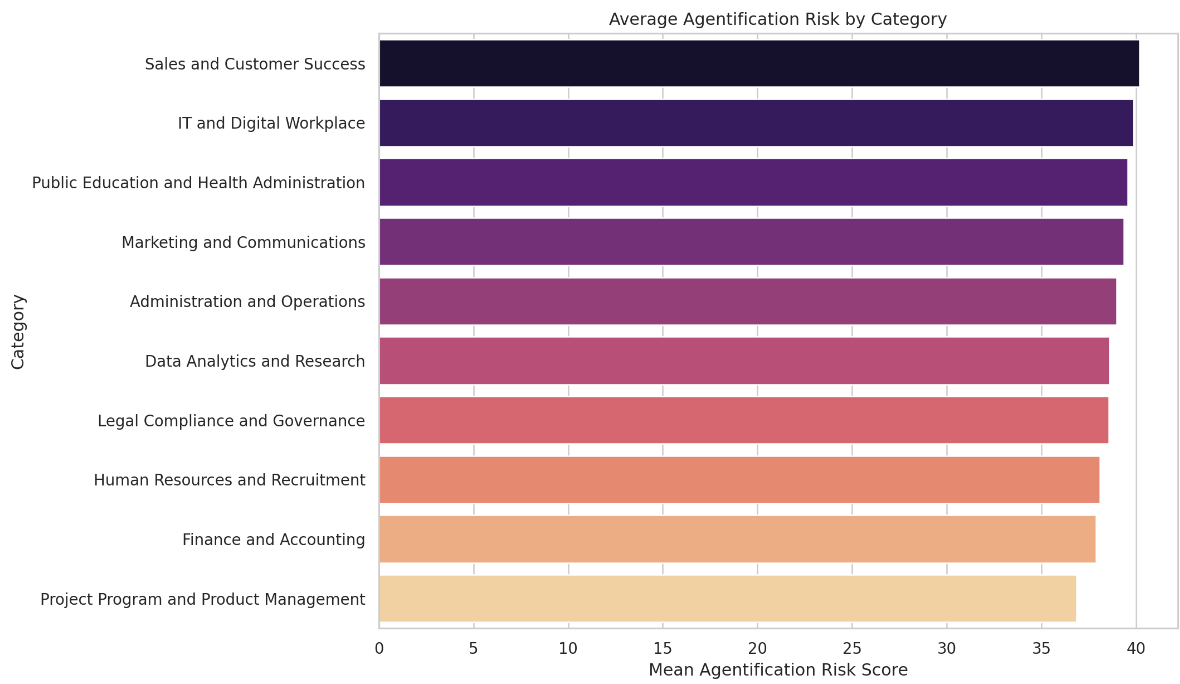

Figure 14

Mean agentification risk by category

The category-level ARS values and component averages are reported in the standalone **Data Appendix, Table D5**.

That **Sales and Customer Success** and **IT and Digital Workplace** rank slightly above more obviously administrative categories is analytically important. It suggests that bounded human-facing workflows and digitally mediated troubleshooting may be especially fertile settings for agentic systems. By contrast, **Project, Program and Product Management** scores somewhat lower on average not because AI is irrelevant there, but because the category carries a larger strategic and end-responsibility overlay, which the model treats as a resistance factor.

5.4 Mechanism Analysis

The risk model separates two related mechanisms: **substitution pressure** and **augmentation pressure**. Substitution pressure rises with structured and repeatable work in Zones I and II. Augmentation pressure rises with the combination of bounded workflows and analytical work in Zones II and III. Many high-risk roles score on both dimensions, which implies that agentification is strongest when workflows can be delegated and reasoning can be scaffolded simultaneously [5].

[Figure 15: Substitution pressure versus augmentation pressure across the role set]

The comparison between **agentic fit** and **overall risk** reveals that some roles are technically well-suited to agentic execution but still buffered by governance-heavy or accountability-heavy work. Others show the opposite pattern: they are only moderately agentic in structure, yet still score high because strategic resistance is relatively weak.

[Figure 16: Agentic fit versus overall agentification risk]

6. Discussion

The empirical pattern observed here supports a more differentiated understanding of AI-driven job redesign. The central finding is not that office work is uniformly easy to automate, but that **agentification potential clusters where workflows are structured enough to be delegated and interpretive enough to benefit from machine reasoning**. This moves the debate beyond the older contrast between routine and non-routine work.

One important implication is that the high-risk segment is not dominated by the most clerical or repetitive jobs alone. Instead, roles with substantial documentation, case handling, scheduling, monitoring, policy interpretation, and coordination often rise to the top. In such roles, value creation depends less on fully autonomous strategic judgment than on sustained progression through information-rich workflows. That structure is highly compatible with contemporary AI agents that can read, write, search, route, summarize, follow policies, and call tools across multiple steps [8] [9].

A second implication concerns governance. Zone IV remains the principal structural barrier to deep delegation. Jobs with strong strategic accountability, institutional discretion, or normative responsibility may still be heavily augmented, but they are less easily surrendered to end-to-end agentic execution. This helps explain why managerial and governance-heavy roles often display significant PASF complexity while ranking lower in net agentification risk.

A third implication is methodological. Because the dataset shows that most office roles are mixed rather than pure profiles, single-label automation narratives are increasingly unhelpful. The PASF approach instead allows analysts to separate the **delegateable**, **augmentable**, and **retained** layers of work. That makes the framework potentially useful not only for academic analysis, but also for enterprise work redesign, job architecture, capability planning, and policy debate.

Marc Drees' review also highlighted several interpretive issues that the unified paper now makes explicit. First, the present formulation works with **four analytical PASF zones**, even though broader PASF thinking may sometimes discuss a fifth layer. In this study, that broader layer was intentionally left outside the operational coding frame because the role-level estimates were designed to separate routine, bounded workflow, interpretive, and strategic-accountability work within a consistently comparable office-work rubric. Second, the study remains primarily **task-based rather than skill-based**. Skills matter, but they are treated here as indirectly embedded within task descriptions and occupational infrastructures rather than as a separate measurement layer. Third, several visually distinctive roles approach almost binary profiles in one or two dominant layers, which is analytically noteworthy and not merely a coding artefact. These clarifications are intended to improve both the interpretability and the reproducibility of the framework.

7. Limitations

The study has several limitations. First, the PASF estimates are derived from structured occupational reconstruction rather than direct observation. They should therefore be interpreted as comparative analytical estimates, not as exact time-use measurements. Second, the role set is deliberately restricted to office and knowledge work in a Netherlands/EU framing. The results should not be generalized without care to manual, craft, field-based, or heavily embodied occupations.

A third limitation concerns the mapping from public occupational descriptions to PASF zones. Although the workflow is systematic, the conversion from occupational tasks to role-level PASF distributions remains a modelling step. The study therefore improves transparency by explicitly documenting the workflow and by separating the full tabular evidence into a standalone data appendix, but it does not eliminate the need for future expert validation.

A fourth limitation concerns references and evidentiary base. The paper now situates itself more explicitly in the task-based labor literature, AI exposure literature, and occupational-taxonomy infrastructure literature. Even so, the internal PASF materials remain an important part of the empirical foundation because the framework itself is still being formalized.

A fifth limitation concerns outliers and low-percentage cells. Some roles show unusually concentrated profiles or small yet non-zero shares in otherwise weak zones. These values were retained because they often reflect real mixed-role composition rather than noise, but they should still be treated as structured estimates rather than precise time-allocation measurements.

A sixth limitation concerns the ARS weighting logic. The current score is deliberately explicit and interpretable, but alternative weighting choices are possible. The model should therefore be read as a defensible first operationalization rather than as a final canonical formula.

8. Conclusion

This paper has shown that PASF can be scaled from a small proof-of-method to a broad empirical mapping of **250 office and knowledge-work roles** in a Netherlands/EU context. The main descriptive finding is that office work is structurally concentrated in **Zone II** and **Zone III**, meaning that bounded workflows and contextual interpretation dominate more than either pure routine or pure strategy [4].

The second and more novel contribution is the **Agentification Risk Score**, which ranks all 250 roles according to the likelihood that a large share of their work can be delegated to AI agents. The ranking suggests that the strongest agentification risk arises where structured workflows, coordination, documentation, and intermediate reasoning overlap, while strong Zone IV accountability remains the chief barrier to deep delegation [5].

Taken together, these results position PASF as a useful intermediate layer between occupational taxonomies, task-based labor research, and emerging debates on AI-driven job redesign. Rather than asking whether a job is simply safe or unsafe, the PASF framework makes it possible to ask a more useful question: **which layers of a role can be delegated, augmented, or retained under agentic transformation?**

9. Future Research

Future work should validate the PASF distributions and ARS rankings with **time-use data, expert workshops, inter-rater reliability exercises, and organization-specific workflow traces**. A second stream should link PASF profiles to actual AI deployment cases, testing whether the predicted high-risk roles are indeed those in which agentic delegation spreads fastest. A third stream should connect PASF more directly to Dutch labor-market infrastructures such as CompetentNL and to sector-specific regulatory settings that shape the governance buffer around different occupations [11] [12] [13].

Appendix A. Agentification Risk Model Notes

The extensive table-based evidence has been moved to the standalone **Data Appendix**. That companion document contains the research questions, workflow stages, PASF category summaries, category risk summaries, top- and bottom-risk tables, the complete PASF role atlas, and the full 250-role ranking. The present appendix therefore retains only the explanatory model notes needed to keep the narrative paper self-contained.

Agentification Risk Model Notes

Concept

This model estimates the probability that a job can be **substantially agentified** rather than merely touched by automation. The score is therefore not a pure routine-automation metric. It combines structured execution exposure, bounded-workflow leverage, reasoning leverage, decomposition readiness, and a negative adjustment for strategic or governance-heavy work.

Formula

The overall **Agentification Risk Score (ARS)** is computed on a 0-100 scale from the following weighted components:

Table 1

Structured summary

Component	Meaning	Weight in ARS
Execution exposure	High weight on Zone I, medium on Zone II, low on Zone III	0.27
Workflow-reasoning synergy	Rewards roles that combine Zone II and Zone III, because such roles are especially compatible with agentic orchestration	0.23
Digital cognition leverage	Rewards analytical and language-heavy work that can be scaffolded by agents	0.20
Agentifiable concentration	Rewards roles whose activity is concentrated in Zones I-III rather than Zone IV	0.12
Decomposition readiness	Uses confidence and normalized task count as a proxy for how clearly the role can be decomposed and assigned	0.08
Strategic resistance	Penalizes roles with high Zone IV shares and high Zone III/IV overlap	-0.20

Interpretation

A high score means a role combines three properties: it contains a large amount of work that is structured or semi-structured enough to orchestrate, it contains sufficient reasoning content to benefit from agentic execution rather than only macro automation, and it has limited strategic end-accountability that would block deep delegation. A lower score does not mean AI has no effect; it usually means the job is buffered by governance, judgment, institutional accountability, or too much heterogeneity.

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