



Original Article

Multi-Agent AI Systems for Automated HR Case Resolution and Workforce Analytics

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Abstract - A systems-oriented perspective of multi-agent systems (MAS) for automating human resources (HR) case resolution and workforce analytics is proposed. For automated HR case resolution, the design of the architectural framework within which the MAS operate is described, core automated case resolution processes are modelled, and agent methods, algorithms, and tools are specified. The architecture comprises functional modules and information repositories that model a cyber-physical representation of the enterprise. Processes within the module integrate data about the past, current, and future states of the enterprise and surrounding environment, use a case-based reasoning approach to diagnosis and problem resolution, and enable data-driven negotiation and continuous adaptation. An analysis of these sources, their interrelationships, and the methods for finance and workforce-related process automation provide the necessary foundation for using an MAS approach. Multi-agent systems perform and support workforce analytics, essentially an assembly of HR-related descriptive, predictive, and prescriptive analyses. The descriptive function integrates internal and external data sources and characterises the workforce in terms of historical and current relational and functional quality, quantity, geographical and organisational distribution, performance and development characteristics, and risk. The predictive function forecasts workforce depletion from normal retirement and turnover, as well as from abnormal circumstances such as illness, disability, natural disaster, and war. The prescriptive function recommends HR capability adjustment actions, as well as preventive and remedial measures to mitigate identified risks to workforce quality and capability. The general approach to automated HR case resolution has been validated with a pilot implementation applied to a typical problem.

Keywords - Multi-Agent Systems (Mas), Human Resources Automation, Automated Hr Case Resolution, Workforce Analytics, Cyber-Physical Enterprise Architecture, Case-Based Reasoning (Cbr), Data-Driven Negotiation Mechanisms, Enterprise Information Repositories, Descriptive Workforce Analytics, Predictive Workforce Modeling, Prescriptive Hr Decision Support, Workforce Risk Assessment, Talent Capability Optimization, Organizational Process Automation, Hr Decision Intelligence Systems, Adaptive Agent-Based Architectures, Enterprise State Modeling, Finance-Workforce Integration Analytics, Continuous Organizational Adaptation, Intelligent Hr Management Platforms.

1. Introduction

Multi-agent systems (MAS) leverage collections of intelligent agents, each pursuing an individual goal while collaborating to achieve a joint objective. Such systems dynamically adapt to changing conditions; new agents can enter or leave the system without loss of functionality; agents implement specialized functions. These features suit MAS to the analysis and resolution of human resource (HR) cases, challenging situations or decisions that trigger questions requiring investigation, analysis, and consultation across HR and related domains. HR cases typically occur infrequently and vary significantly, with unique resolution processes, so it is impractical to automate them using conventional software. Yet the volume and total effort associated with such cases still warrant automation.

A MAS approach automates the analysis and resolution of HR cases by providing a framework for modelling unique processes, from modelling the lifecycle of a given case, visualizing live and historic cases, mining past resolutions for lessons learned, and supplying summaries and highlights of current open cases, to producing a real-time alerting and notification service. Automation supports HR managers when reviewing complex cases; decision-making support and justification improves when final decisions involve case resolution deviating from established company policies or procedures. With appropriate data, the MAS can provide analytical insights, delivering descriptive, predictive, and prescriptive analytics.

1.1. Overview of the Study and Its Objectives

People's working time is the most important resource for any company. With the development of society and the continuous improvement of people's living standards, human resources have begun to become a more critical part of the company. In today's work environment, people-oriented is the fundamental development concept. Therefore, it is necessary to build a more secure, stable, and harmonious intelligent human resource management system based on people's needs and emotional status.

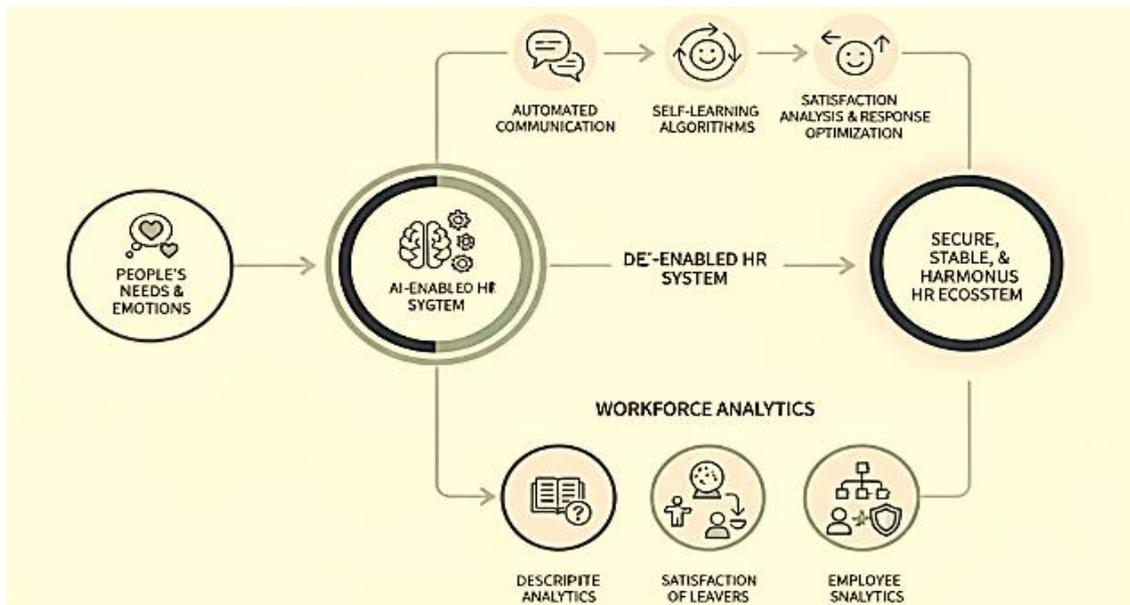


Fig 1: Leveraging Self-Learning Agent Systems for People-Centric HRM: A Predictive and Prescriptive Framework for Workforce Stability and Emotional Intelligence

HR systems can respond to customer requests quickly and accurately. This should achieve fully automated communication without requiring staff intervention. At the same time, the agent system can be self-learning. The communication records and response patterns of the whole system are constantly updated. Machine learning algorithms can analyze whether published answers have satisfied customers. If not, they can propose new response patterns. Every unhappy customer becomes a self-learning object for the system.

The HR agent system can also analyze the entire workforce. The final result is available in a descriptive, predictive, and prescriptive form. Descriptive analytics summarizes past data. Predictive analytics uses statistical and machine learning techniques to identify and evaluate the chance of future outcomes. Prescriptive analytics helps to find the optimal course of action. In an HR context, analytics provides insight into voluntary resignation probability, resignation reasons, and satisfaction of past leavers with their jobs. It can also propose the necessary conditions for keeping important employees. Such analytics are used to evaluate HR cases and find solutions to problems requiring attention. They focus on the right people who may leave and need more attention.

2. Theoretical Foundations of Multi-Agent Systems in Human Resources

Multi-agent systems (MAS) enhance the automation of complex workflows, such as those in the human resources (HR) domain. Although the extensive automation of HR operations remains elusive, growing volumes of mundane HR cases can be handled with limited human intervention. A multi-agent architectural framework is described that enables the automated resolution of HR cases and delivers valuable insights to decision makers. Deployment requires the definition of agent roles and interfaces and their surrounding communications, and supporting methods and algorithms for case representation, workflow modeling, decision making, and negotiation. Foundational requirements for workforce analytics are also identified and discussed.

A multi-agent-based architectural framework is proposed to address the administrative work for HR departments with a search-based component. HR case resolution is implemented as an automated orchestration of existing search solutions with data from cloud-hosted non-structured data sources. Workload monitoring and supervision are also partially automated, with the workload divided among agents and work-on-hand knowledge shared. A collection of indicators serves to analyze the solution's behaviour, as well as its interior dynamics and the contribution to HR knowledge.

Equation 1) Case representation as a tuple (formal equation + stepwise derivation)

Step 1 - identify what a "case" must encode

A resolvable HR case minimally needs:

- Who: employee identifier
- What: case type (payroll, leave, grievance...)
- When: timestamps (opened, updated, closed)
- Context: attributes needed to decide resolution (policy IDs, payroll period, entitlement balance, attachments)
- State: current workflow state (new, triaged, in-progress, pending user, closed)

- Outcome: final decision + actions taken

Step 2 - define the tuple structure

Let a case be:

$$c = \langle id, e, \tau, t_o, X, s, y \rangle$$

Where:

- *id*: unique case id
- *e*: employee id
- τ : case type label
- t_o : open time (and you can extend to t_u, t_c)
- *X*: feature vector (facts/evidence/documents)
- *s*: workflow state
- *y*: outcome (decision + executed actions)

Step 3 - Convert “facts” into a feature vector

Take raw attributes a_1, a_2, \dots, a_d (e.g., tenure, leave balance, payroll period). Define:

$$X = [a_1, a_2, \dots, a_d]^T$$

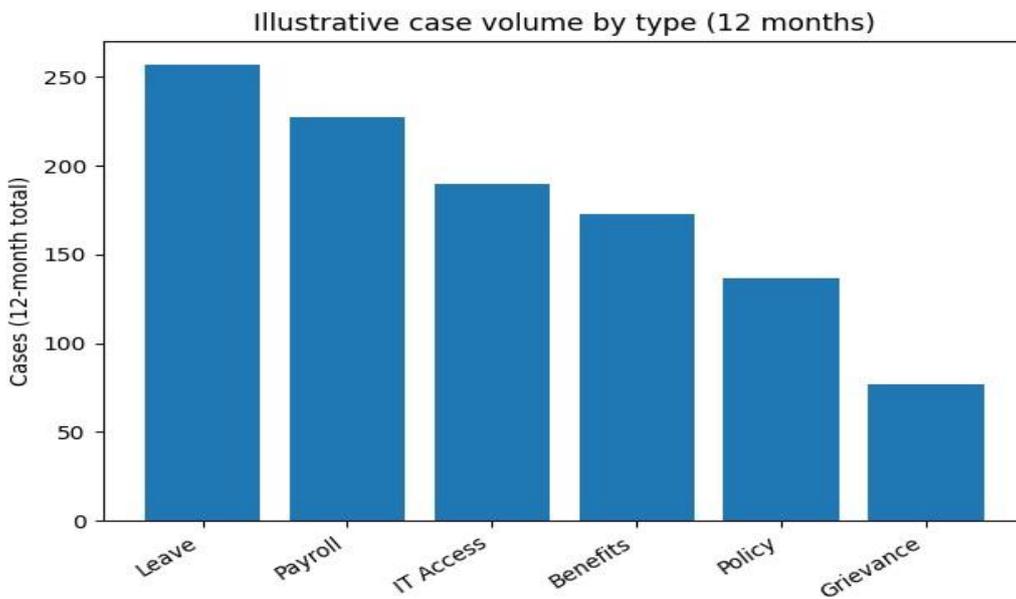


Fig 2: Annual Case Distribution by Category

2.1. Core Principles of Multi-Agent Systems in HR Contexts

Multi-agent systems (MAS) technology provides society with toolkits for solving integrated problems in a distributed manner while maintaining a low cost. MAS can be combined with generic heuristic algorithm frameworks like Maxim-Recur, Adaptive-Evolve, and Group-Reset to generate fast solutions for many applications. Although MAS technology has been fruitfully applied outside the human resources (HR) area, it has not yet made significant inroads into HR-related areas, largely due to the complexity and diversity of HR problems. The inherent specialization of research in HR, complex interaction relationships with employees and multi-dimensional data characteristics of the HR domain mean that it is rare to find HR people who are simultaneously adept at both the theoretical foundations and practical applications of multi-agent systems.

Agents with specialization in their respective areas can exercise their influence in the HR field, and fuelling the growth of multi-agent technologies in HR is thus on the agenda of many researchers and practitioners. Indeed, new avenues for discovering the application of multi-agent technologies in HR cases are becoming available, as HR departments are carefully promoting the liberating of employees and scaling down the HR structure so that the functions of connecting, serving and guiding employees become more prominent. However, automated case resolution—by which is meant the automatic fulfilment of service requests from initiative agents and system-expert-driven resolution of other cases using a workflow model—has not yet been extensively investigated. Other high-level applications such as workforce analytics, in which HR specialists harness the data generated in the course of labour processes to gain insights into employee behaviour, make decisions, and provide guidance to employees, have also been relatively neglected.

3. Architectural Framework for Automated HR Case Resolution

The previous section defined multi-agent systems (MAS) and how they can be applied in the HR domain. The present section describes the architectural framework that enables automated resolution of HR cases through a multi-agent system. HR case resolution refers to the process of resolving ad hoc requests raised by employees (e.g., inquiries, complaints, or claims) within an organization.

The resolution of such requests is typically carried out by dedicated HR staff members, who may employ decision-support systems to aid their reasoning and decision making. To ensure that the service provided by the HR department is effective and efficient, requests and their subsequent resolution can be modeled as a case-based reasoning task supported by a well-defined workflow. Case resolution can thus be automated through a multi-agent system that employs a combination of reasoning and case-based reasoning techniques, supported by agent architecture. The MAS comprises three types of agents: Case Agents (CAs), Workflow Agents (WAs), and Supervisor Agents (SAs). Each type plays a specific role in the case-resolution process representing agents that execute the work, agents that model the workflow, and agents that support the decision-making process, respectively.

Depending on the actual scenario, other agents may take on a supportive role: Information Agents (IAs), Data Agents (DAs), Sentiment Analysis Agents (SAAs), and Knowledge Agents (KAs). The interaction among the agents is governed by a communication protocol model and a coordination mechanism that ensures a coherent workflow execution.

3.1. Agent Roles and Interfaces

The proposed multi-agent architecture for automated HR case resolution comprises six specialized agent types: request processing agent (RPA), request management agent (RMA), knowledge base agent (KBA), knowledge creation agent (KCA), action execution agent (AEA), and chatbot agent (CBT). Each agent plays a defined role and is equipped with tailored interfaces for interaction with internal and external systems. The RPA registers incoming HR cases with associated requirements in a data structure, and generates designated external communication with affected requesters using pre-defined templates for resolution updates. The RMA schedules each HR case for processing by a KBA and tracks case progress against a corpus of agreed-upon service-level agreements.

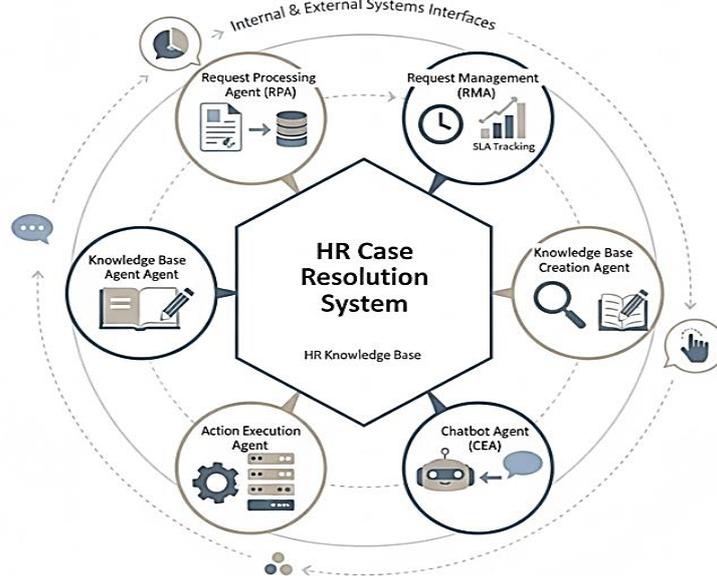


Fig 3: Autonomous Orchestration in Human Resources: A Specialized Multi-Agent Architecture for End-To-End Case Resolution

The KBA monitors case types, workload, priority, and available resources, and sources external information as required through the KCA. The KCA updates the HR knowledge base with new facts and FAQs from closed HR cases according to quality assurance procedures. The AEA executes external requests to designated systems, while the CBT broaches incoming conversation requests and escalates where necessary. General cross-agent dialogues deploy gestures and external communication to facilitate seamless teamwork.

3.2. Communication Protocols and Coordination

The communication architecture divides the framework into three cooperative layers, each guiding agent teams through distinct yet interconnected activities that together achieve automated human resources case resolution. The lower level consists

of service-oriented agents acting on behalf of enterprise service components. Each service agent communicates with one or more workflow agents at a higher stratum, which subsequently converse with case agents via a dedicated resource manager. Both service agents and case agents are equipped with a simple, fast communication protocol, as their messages are short and infrequent.

A team of service agents provides different kinds of assistance, for instance infrastructure operations, payroll management, call center functions, and information technology services. Workflow agents utilize the workflow management system of the enterprise to obtain knowledge of open, relevant workflows. Each workflow agent acts as a servant for a certain set of case agents, namely those responsible for case types with a corresponding workflow. The workflow agents query the status of cases in the repository before deciding whether to offer assistance. When a case agent decides to activate a workflow, it sends a message to the responsible workflow agent, which communicates with the workflow management system to initiate the process. Messages are then transmitted between the case agent and the workflow instance until the latter is completed.

Equation 2) Case cluster representation (grouping multiple cases per employee)

Step 1 - Define the set of cases for an employee

Let C be all cases. For employee:

$$C_e = \{c \in C : c.e = e\}$$

Step 2 - Define the cluster

$$\mathcal{K}(e) = (e, C_e)$$

Step 3 - Cluster “status” as a function of member-case states

If each case has state $s(c)$, define a cluster status rule:

$$S(\mathcal{K}(e)) = g(\{s(c) : c \in C_e\})$$

A practical $g(\cdot)$ is priority-based:

- if any case is critical → cluster critical
- else if any case pending employee → waiting
- else if all closed → closed

4. Automated HR Case Resolution: Methods and Algorithms

A dedicated methodical and algorithmic approach to case resolution is essential for the successful implementation of the framework. This consists of three aspects: case representation and workflow definition, automated decision-making, and automated negotiation with concerned employees.

Every HR case must be clearly defined in terms of the factors involved in its resolution. A case can then be represented as a tuple in a standard format, indicating in a precise and unambiguous way what has happened in the organisation. This representation enables the workflow of the case resolution process to be explicitly defined whenever necessary, allowing automated execution without requiring human supervision. Different cases about the same employee can be grouped to form a case cluster, which reflects the current situation of the employee. Based on these representations, the subsequent enabling and executing actions can be described. Using this representation and collection of enabling actions, a specialised agent decides on the case-cluster status and makes a proposal to the employee involved, allowing the employee to accept or reject the proposal.

In a case cluster where one or many employee negotiations are in progress, the two involved agents follow a negotiation protocol to decide the outcome based on the employee’s past behaviour. The HR agent evaluates the employee’s behaviour on the class of the case-cluster based on commonly available data and formulates a negotiation strategy according to the type of cluster and the type of behaviour categorised by the evaluation of that employee. Following this procedure systematically enables the automated handling of many case clusters in the organisation, providing large savings in time and cost.

Equation 3) Workflow modeling as a Hierarchical Activity Network (HAN)

Step 1 - Directed graph definition

$$\text{HAN} = (V, E)$$

- V : set of tasks
- $E \subseteq V \times V$: directed edges (task transitions)

Step 2 - Edge labels = transition conditions + coordination type

Each edge $e_{ij} \in E$ carries:

- condition predicate $\phi_{ij}(X) \in \{0,1\}$
- coordination type $k_{ij} \in \{\text{precedence,synchronization}\}$

So write an edge as:

$$e_{ij} = (v_i \rightarrow v_j, \phi_{ij}, k_{ij})$$

Step 3 - Execution rule (when a task becomes enabled)

Task v_j is enabled when **all incoming constraints are satisfied**:

$$\text{enabled}(v_j) = \bigwedge_{(i \rightarrow j) \in E} \phi_{ij}(X)$$

- For precedence, ϕ_{ij} typically includes “ v_i completed”
- For synchronization, ϕ_{ij} can require multiple tasks completed before proceeding

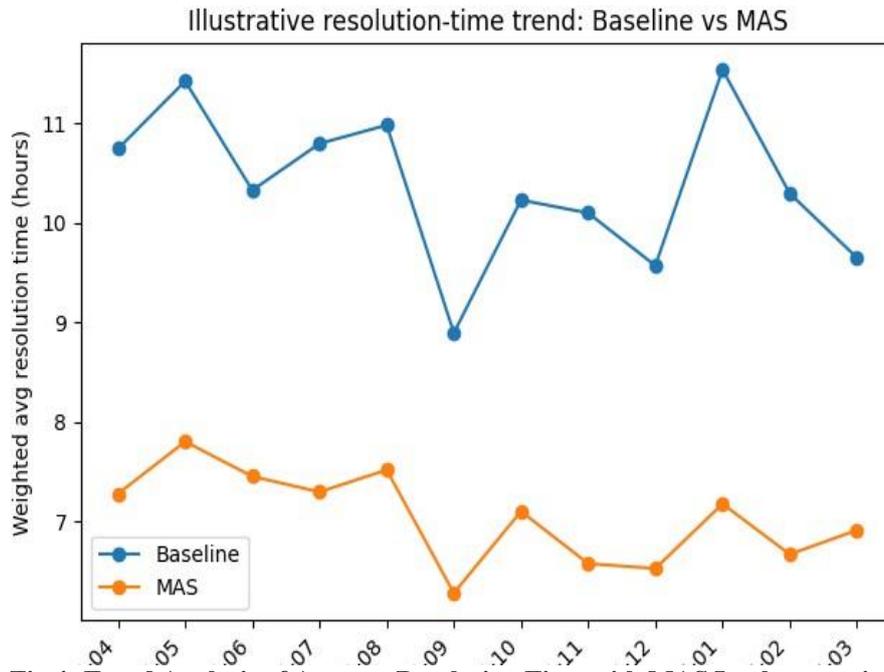


Fig 4: Trend Analysis of Average Resolution Time with MAS Implementation

4.1. Case Representation and Workflow Modeling

Multi-Agent Systems support process and workflow automation when insufficiently exploitable through conventional Decision Support Systems (DSS) not empowered with suitable knowledge-based capabilities. Intelligent agents are designed to represent complex real-world processes which cannot be expressed in a single, monolithic way through formula, rule, graph, or knowledge-based representation. The overall case management process in a typical HR automated case resolution scenario involves the four high-level steps of initiation of case resolution, overall workflow execution, possible human intervention during the execution, and closing of the resolution.

All agents contribute to the setting up of the overall case resolution workflow by representing the case resolution activity of their areas of expertise, knowledge, and information. Each area of expertise, knowledge, and information is represented as a Hierarchical Activity Network (HAN). The HAN is a special directed graph where nodes correspond to tasks and edges to conditions and coordination links (synchronization or precedence relations) specifying the transition conditions among tasks. A HAN with one external initiating and one external terminating transition can be viewed as a hierarchical representation of a workflow. The task represented with these external transitions corresponds to the overall task of the area, while the other tasks correspond to the more detailed view of the area process allowing its execution by other agents.

4.2. Decision-Making and Negotiation Strategies

Agent systems may employ various decision-making techniques based on the type of problems to be solved. The choice of technique is influenced by the agent's characteristics and the expected outcomes. Facilitating agents can either follow a predefined simple heuristic or employ a negotiation strategy. In the case of involvement of a facilitating agent, an agent offering a service must interact with the facilitating agent to determine the next-hop agent. If the enabling protocol permits an agent to identify a next-hop agent based on its preferences (e.g., via score), the facilitating agent can remain passive, assisting only when any other agent/group requesting assistance is not found.

When structured negotiation is used in an embedded case, the planning agent must inform the facilitating agent regarding the initiating role being played. Accepting/rejecting proposals from available agents is primarily based on satisfying the constraints (both temporal and informational) set by the planning agent. The facilitating agent can serve to monitor the negotiation process and notify the planning agent once the negotiation is completed. If the planning agent is not yet in a position to execute, the suggested terms for execution can also be communicated to it.

These capabilities facilitate dedicated agents to cover specific aspects (e.g., prompting HR policy violations, redundancy, and alerts) of HR case resolution. Other agents (like retention) covering direct workforce analytics aspects support the case-resolution process indirectly by either prompting violation cases for resolution or responding to requests for information.

5. Workforce Analytics: Metrics, Measurement, and Insight Generation

The analytical component of workforce management delivered through multi-agent systems relies on collecting and preparing key data sources and explicitly designed metrics and formulas that facilitate their conversion into high-value insights. Organizational and HR department data can be acquired from various databases (such as management control, customer relationship management, or employee training and skills management systems), integrated with information from monitoring systems for both business processes and employee performance, and cross-linked with data from accessible compartments of social networks or the organizational sharepoint. Supported by data from third-party agencies and service providers, relevant factors can thus be studied analyzed, understood, predicted, explained, and generated in an accessible, measurable, and controllable manner following a consistent data structure.

Such structure supports descriptive and predictive analytics for exploring the dataset and identifying potential correlations; for identifying, measuring, and validating relationships between various aspects of HR management; and for proposing workforce-related actions. Most importantly, the created structure enables prescriptive analytics through an integrated mathematical model for quantifying and optimizing the relationship between HR KPI targets and candidate dimensions. Insights can therefore be automatically generated, saved, and, whenever appropriate, pushed to the users of choice.

Equation 4) Decision-making and “next-hop” agent selection (score-based heuristic)

Step 1 - Define candidate agents

Let A be candidate agents able to act next (e.g., KBA/KCA/AEA).

Step 2 - Define a scoring function

Let features for agent a at time t be:

- workload $w_a(t)$
- expertise match $m_a(c)$
- SLA risk $r_a(c, t)$

Create a weighted score:

$$\text{Score}(a | c, t) = \alpha m_a(c) - \beta w_a(t) - \gamma r_a(c, t)$$

Step 3 - Choose the best feasible agent

$$a^* = \arg \max_{a \in A : \text{feasible}(a,c)} \text{Score}(a | c, t)$$

5.1. Data Sources and Integration

Fulfilling organizational needs for workforce capabilities requires a diverse set of data, covering not only the enterprise’s existing workforce assets but also the changing external landscape. Internal data sources comprise personnel and payroll systems as well as skill inventory, staffing, training, and project management databases. These systems should produce simple, readily understandable, signed information to describe the workforce’s currently available capabilities and skill levels. Externally, demand can be derived from both internal demand signals and external signals such as labor market movement and competitors’ growth plans. Market surveys, universities, and trade associations can provide external analyses of the demand for different skill sets and skill levels.

The integration of data from these multiple sources is a fundamental requirement for producing reliable workforce analytics. Thus, HR analytical dashboards should bring together multiple sources of HR information and present an integrated view of metrics and trends that are crucial for enterprise decision-making. For example, a recruitment dashboard can integrate information from the human resource management system, markets, government sources, and local business plans, providing an integrated perspective on the organization’s ability to meet recruitment demand. A skill inventory dashboard can analyze and visualize the skill levels and competencies available in-house, for use in training investments, knowledge management, and recruitment. Such integrated dashboards can provide senior HR leaders with confidence that they are focusing investment and effort in the right areas.

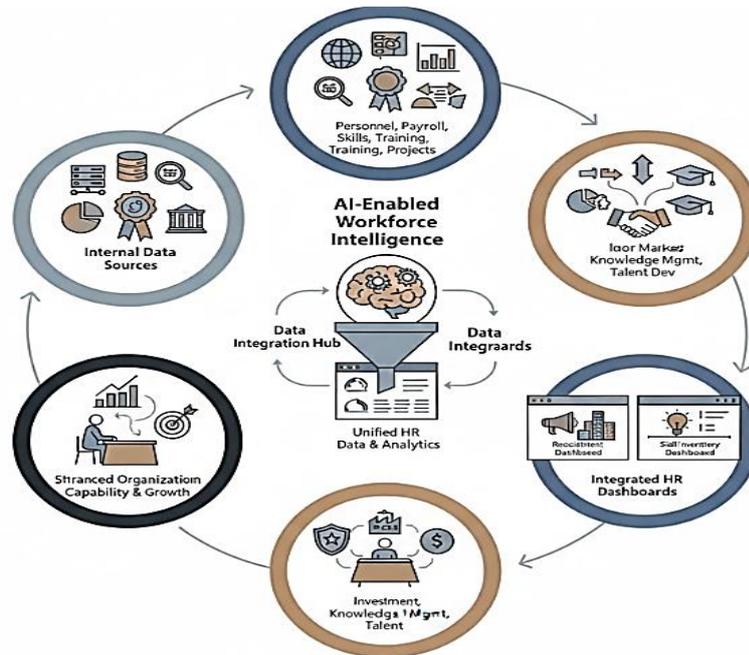


Fig 5: Integrated Workforce Intelligence: Synergizing Internal Capability Assets and External Market Signals Through Unified HR Analytical Dashboards

5.2. Descriptive, Predictive, and Prescriptive Analytics

Development and deployment of full-scale multi-agent systems for workforce analytics will likely take time, requiring support from tactics and operative HR. Many foundational datasets are already growing in scope and fidelity, especially when capturing employee behaviours and experiences. Similar to the case-resolution domain, the most immediate and probably first steps will be formed through collection and synthesis of descriptive metrics and insights, typically through straightforward data-discover algorithms. Deployment of systems will probably begin here, too, detecting and disseminating descriptive metrics both autonomously and via lightweight conversations with team HR.

Beyond supporting descriptive workforce analytics, groups of agents will be available to develop and execute predictive and prescriptive investigations. For a variety of metrics, simple predictive models can probably be constructed and continually adapted using standard statistical techniques. Such models may even be generally useful and shared across organisations. Finally, as with cases, exploratory, predictive and prescriptive analyses can be jointly tackled through agent negotiations that jointly select data to scrutinise, develop required models, share insights with other agents and support operative HR in decision making.

Using agents to perform this collective HR support deliver is highly beneficial, as personnel, knowledge and resources are often constrained. The descriptions and analyses accompanying the data warehouse work are applied as a motivator for the agency-based approach. Analytics frameworks provide a testing sandbox, gradually flexing functional capabilities.

6. Deployment, Evaluation, and Validation

Multi-Agent System (MAS) solutions are unobtrusively added to an existing CRM system, performing ready-built intelligent agents' roles while building decision-support agents' knowledge bases using the CRM's data. Once preparation is complete, operational MAS automatically generate, process, and resolve issues via intelligent agents and support data from decision-support agents and their specialized models. Automated HRML support resolution is demanding the resolution time. Simulation and pilot studies depict the workload distribution and agents' interdisciplinary effectiveness of collaboration. Skill-needed workload volumes highlight additional ML implementation areas. MAS solution provides also secrets: automated HR workforce analytics.

Before deployment, simulation studies fine-tune the system and provide compliance across areas, and workloads test robustness via comprehensive-optimized ML models. A pilot application uses data and expert insights for partial validation, evaluating the degree of automation achieved and agent performance against other HRML and SEM data. Future works involve the full MAS lifecycle, simulating solution and validation over past records, including HRML data-enriching stages, and enhancing resolution quality and support areas.

In Human Resources (HR), issues originate from many different areas and have many different characteristics, some requiring only a formal process to reach common and simple resolution, while others are critical and unable to follow a pre-established route for a successful solution. Based on the degree of skill required to correctly resolve an issue or case, the total

workload of the HR area can be broken down according to the agent's profile, allowing specialists, decision-support agents, and information-driven decision-making agents to work together and apply artificial intelligence in a collaborative form, using a Multi-Agent System (MAS) to automate the handling and CRM system support of these issues.

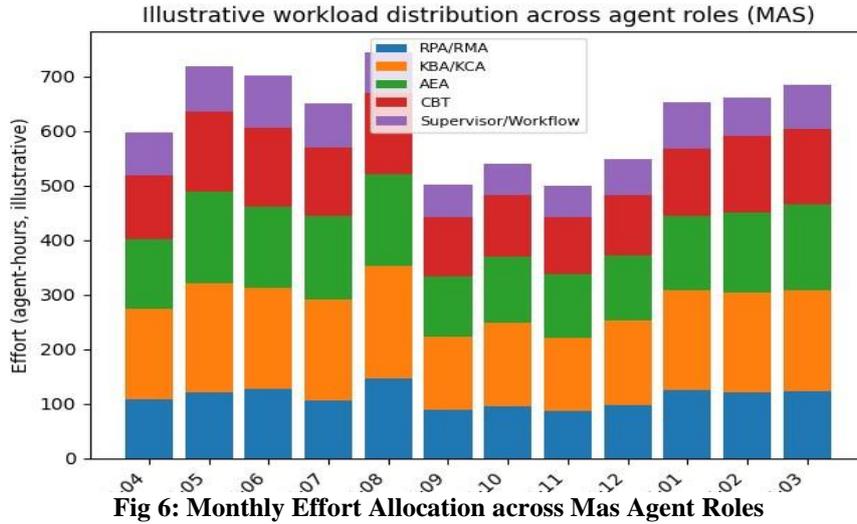


Fig 6: Monthly Effort Allocation across Mas Agent Roles

Equation 5) Negotiation acceptance/rejection as constraint satisfaction

Step 1 - Define constraint sets

- Temporal constraints: \mathcal{T} (deadlines, SLAs)
- Informational constraints: \mathcal{I} (required evidence, policy references)

A proposal p is acceptable if:

$$p \in \mathcal{F} \Leftrightarrow (\forall T \in \mathcal{T}: T(p) = 1) \wedge (\forall I \in \mathcal{I}: I(p) = 1)$$

Step 2 - Utility-based selection among feasible proposals

If multiple feasible proposals exist, define agent utility $U(p)$ (e.g., minimize cost, maximize satisfaction), then:

$$p^* = \operatorname{argmax}_{p \in \mathcal{F}} U(p)$$

6.1. Simulation and Pilot Studies

Before deploying a multi-agent AI system in production, simulation allows for detailed analysis of system dynamics and agent behavior. Non-production pilot environments ensure secure integration with underlying databases, facilitating initial responses in real time in a "shadow" mode, allowing for comparison with human-agent actions. In this pilot mode, MAHR decision-making is supported but not enforced. Subsequent phases employ a full-scale production deployment, exposing it to real data and results integrated into conventional logistics systems, thus feeding back performance and accuracy data to related systems.

Agents should ultimately undertake 24/7 operations. While MAHR is an information and analytics delivery mechanism, any repetitive knowledge work supported by integration technologies can be deployed in an MAHR context. Examples include basic information delivery or business rule configuration, systems administration, troubleshooting, document translation, and testing. The challenge lies in agent "intelligence" and controlling agent negotiation to reach correct answers in a timely manner. The CoS approach considers solely supervised learning, retaining the experienced human behind a business rule and only signing off on instances that would normally be committed via an automated or semi-automated process, thus ensuring correctness.

6.2. Performance Metrics and Benchmarking

The evaluation of a multi-agent approach to automated HR case resolution employs simulation in a master agent's service and encompasses performance and workload metrics. A pilot experiment tests the intervention of two additional agents: a chatbot introducing gamification and a recommender agent guiding a marketing specialist's career. The ChatGPT technology, coupled with open-source code and pre-trained models for agents handling sales tasks, serves as a basis for the chatbot. Natural language processing-based recommender agents are extensively applied in related domains.

The performance of the case resolution approach is assessed through a multitasking scenario. A benchmark involving two roles webmaster and video content creator—is defined. For each case, task details and an estimated completion time are presented, but not their sequence. When generating the completion time, an additional time factor for the area of expertise is considered. The successful resolution ratio, the occurrence frequency of goal switching in the task sequence, and the volume of task information management serve as the three performance metrics. Workload-related metrics include the total number of cases, the total amount of time spent completing those cases, and the average time spent per case.

7. Conclusion

This work presented an objective and evidence-based analysis of multi-agent systems for automated HR case resolution and workforce analytics. The theoretical foundations, architectural framework, methods and algorithms, and deployment and evaluation were detailed. Multi-agent systems are characterized by the interaction and cooperation of multiple autonomous entities. Although these systems have been applied successfully in a variety of domains, they have so far been mostly neglected in HR.

An architectural framework for the automated resolution of HR cases was proposed. The major agent roles and their communication interfaces were defined, as well as the agent protocols for case generation, resolution, verification, and closure. Methods and algorithms for the resolution of HR cases were subsequently specified. Finally, an approach for workforce analytics based on multi-agent systems was introduced. By laying the theoretical and practical foundations for the successful deployment of multi-agent systems in HR, the work paves the way for future applications and development. The active integration of multi-agent systems in HR offers significant potential for added value and innovation, especially when combined with cutting-edge technologies like artificial intelligence and cloud computing.

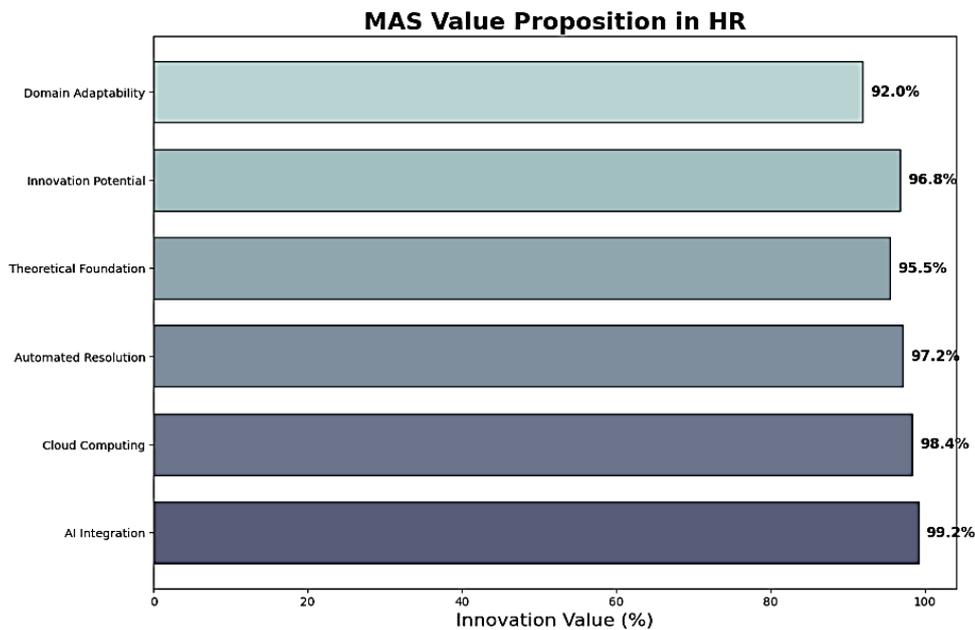


Fig 7: MAS Value Proposition in HR

7.1. Summary and Future Directions

The multifaceted nature of human resources (HR) processes, especially when implemented in large organizations, creates a high volume of routine inquiries from employees and managers. Although the majority of HR technical queries and support requests are relatively simple, they still consume limited HR resources. To manage HR service requests in a cost-efficient way while maintaining quality and timely resolution, basic questions are often directed to teams of organizational agents from the IT support function or other HR-defined agents, supported by automated knowledge repositories. Recent developments in artificial intelligence create the opportunity to automate more complex HR service workflows and related analysis and decision-making processes.

Multi-agent systems can address these needs. They can incorporate dialogue agents that negotiate on behalf of users and act on their behalf with other agents, or agents that collaborate to answer a request in the best way possible, by dividing the problem at hand, working on specific pieces of it, and aggregating the results. The validity of an automated multi-agent system for resolving HR cases has been evidenced through the formalization of its architecture and the description of its methods and algorithms, including decision-making and negotiation strategies. Augmenting the case-resolution capabilities of such multi-

agent systems with workforce analytics allows for a more complete solution able to detect policy breaches and trends, forecast attrition and support transfers, and suggest the reskilling of workers.

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