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Leveraging Ontologies and Process Mining in Personalized Recruitment Recommendations

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Abstract This paper presents a novel approach to improve recruitment methods through a comprehensive examination of contextual data and process models. The primary focus is on refining the process by aligning it with candidate preferences. The method incorporates ontology and process mining to provide contextual and sequential recommendations, adapting hunting methods according to candidate requests. Using a recruitment ontology and connecting it with candidate assessments, the approach refines strategies using successful recruitment historical data. Conformance checking identifies similar process models, connecting the ontology of each activity for a detailed analysis. The results highlight the effectiveness of the method in adjusting recruitment strategies based on historical and contextual data, offering a comprehensive and flexible solution for efficient recruitment.

Keywords Semantic process mining, Ontologies, Event-logs, Recruitment optimization

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1. Introduction

The recruitment process plays a key role in enabling the 8th and 11th Sustainable Development Goals (SDGs)[†], which focus on fostering inclusive economic growth and sustainable cities and communities. The 8th SDG promotes decent work and economic growth through job creation, while the 11th SDG supports access to sustainable urban environments, achieved through strategic recruitment that contributes to resilient, inclusive communities. Recruitment agencies and HR departments are continually optimizing hiring processes to attract top talent while minimizing costs and time, a challenge compounded by the industry's nature [12].
These agencies serve as the critical bridge connecting job-seeking candidates with companies seeking employees. They face persistent challenges in achieving optimal candidate-job matching, leading to: high employee turnover rates resulting in financial losses for companies and disruption of operations, lengthy hiring times causing delays in project execution and missed opportunities and mismatched placements leading to employee dissatisfaction, decreased productivity, and negative brand perception [5].
Numerous studies have explored how technology can streamline the recruitment process, enhance candidate screening, and improve matching accuracy [2, 1]. However, the intersection of ontologies and process mining remains an underexplored domain, presenting significant potential for innovative solutions. Despite the growing interest in process mining, the incorporation of ontological structures to enhance the understanding and representation of complex processes is not extensively investigated. In the context of recruitment, there is a notable absence of ontology-based solutions, limiting the ability to model and analyze intricate relationships within this dynamic domain. This gap in research underscores the need for a more comprehensive exploration of

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†https://sdgs.un.org/goals

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the synergy between ontologies and process mining, especially in specific application areas like recruitment [46, 9].

The presented paper contains a new methodology that combines ontologies with process mining in order to generate custom recruitment recommendations. The proposed approach introduces an ontology-based framework to model the complex relationships within the recruitment domain, which is used to get a more detailed and more accurate representation of the dynamics of candidates and jobs. Process mining techniques are used to analyze recruitment event logs, which in turn, allows for actionable insights to optimize hiring workflows. These components are further utilized to build up a personalized recruitment recommendation system that upgrades candidate-job matching, tested through a real-world case study to verify its practical effectiveness and scalability.

The methodology that is suggested in this paper, in comparison with the one that exists already, stands as very promising. The combination of ontologies with process mining leads to more accurate matching through gaining a deeper understanding of candidate profiles and job requirements, which are far beyond traditional AI-based solutions. The use of process mining not only makes the process dynamic by allowing for continuous improvement on the part of the recruitment teams but also represents the best way to stay ahead of the constantly changing technology usage in the industry. Furthermore, the ontology-based framework is a comprehensive representation of knowledge that is domain-specific, meaning it captures domain-specific insights that are often forgotten in purely data-driven systems. These new features are together employed to solve the most challenging problems in the recruitment industry and, thus, make the hiring process more powerful and sustainable.

The remainder of this paper is structured as follows. Section 2 introduces the key concepts of event logs, process mining, and ontologies within the recruitment context. Section 3 critically examines existing research, highlighting the gap in ontology-based solutions. Section 4 details the proposed methodology. Section 5 presents a case study demonstrating the effectiveness of our approach. Section 6 discusses findings and implications, while Section 7 summarizes key takeaways and future research directions.

2. Background

2.1. Factors Influencing the Recruitment Process

Finding the right candidates can be challenging, and it is a multi-factorial issue. The job position requirements, which are critical for defining the position-specific the skills, qualifications, and experiences, are some of the key factors [17]. Keeping up to date with industrial trends like new technologies, methodologies, and skill demands, is an indispensable factor to make the recruitment strategy flexible [41]. Besides the familiarity of technology, the company's culture is one of the significant areas that are addressed, i.e. successful recruitment should mainly flow with the organizational culture and convey the values, work environment, and ethos of these organizations [3]. The recognition of the demographics and transnational backgrounds of candidates makes it possible to develop recruitment strategies that convince nearly all potential hires [25]. The working of a geographically rooted company can partly affect the talent availability and the way of sourcing and attracting people [38]. The current workforce can truly make the most out of the new AI tools, social media, and applicant tracking systems as they become more and more advanced, offering companies the ability through [35]. Diversity and Inclusion are the main focus indicating the need to get rid of biases and establish an inclusive environment [37]. The situation of the job market, the competition level, salary levels, and how the overall economy is doing will then set the targets for the candidates and the companies such as the job market competitiveness, salary expectations, and overall economic climate must be kept in mind when making the [4]. Legal and regulatory compliance facilitates the ethical and lawful hiring of new employees, regulates the alignment of recruitment strategies with labor laws and regulations [11]. The competitive landscape and the analysis of competitors' strategies should be taken into account in order to show the unique selling points the company has and attract the best [20]. These factors are the ones that mold the overall recruitment practice having both top-down and bottom-up strategies which in essence are the major factors of attraction, assessment, and selection of the right candidates within the organization.

2.2. Hunting Methods

Recruiters use a variety of techniques to find and engage the right candidates for job openings, utilizing effective strategies to meet their needs [32, 29]. Online job boards, such as LinkedIn, Indeed, and Glassdoor, allow recruiters to actively post openings and search for candidates [30]. Social media recruiting, particularly on LinkedIn, enables engagement through network expansion and participation in relevant groups [8]. Networking events offer opportunities to build relationships with professionals and industry influencers. Employee referrals are often encouraged through incentive programs, leveraging the existing workforce's networks. Headhunting or executive search involves proactively approaching passive candidates and utilizing specialized firms for high-level roles [31]. University and college recruitment focuses on attending career fairs and partnering with career services to connect with entry-level talent. Recruitment agencies provide external expertise to efficiently fill specific roles. Company websites and careers pages serve as direct portals for applications, while Boolean search techniques enable precision in identifying candidates with specific skills. Industry-specific platforms cater to niche skill sets through specialized job boards. Talent pools and pipelines are cultivated for future hiring needs, ensuring a steady supply of potential candidates. Collaboration with professional organizations enhances visibility and attracts talent within specific fields. Effective recruiting often combines these methods, tailored to the organization's goals and the characteristics of the target talent pool.

2.3. Process Mining

Process mining is a data-driven approach that analyzes event data to uncover details of operational processes. Using advanced algorithms, it finds trends, patterns, and specific flow characteristics. It aims to transform event data into actionable insights. Across various industries, process mining can help simplify procedures, identify improvement opportunities, and ensure systems function as intended [45].

2.3.1. Event Logs Event logs, in process mining, are detailed and time-stamped records of events or activities occurring within an organizational process (See Figure 2). Each entry in the event log captures essential information such as the type of activity, the entity performing the action, the timestamp of when the activity occurred, and potentially other relevant attributes. These logs serve as a chronological record of actions and transitions, providing the raw data required for process mining algorithms to analyze, model, and visualize the workflow of a given process [44]. They play a crucial role in uncovering insights, identifying patterns, and optimizing organizational processes through the application of process mining techniques. In contrast, traditional birth registries or human-reported data do not have the actual response or correct time reference such data sets as the event log has, which is the main attribute of objectivity. With an event log, the recruitment process flow is depicted by objective, neutral, third-person statements established by computers and lasted beyond the span of the participant's memory and his or her biases [40].

An activity record in the event log refers to a step performed in a certain process instance (referred to as a trace). To simplify this process, we list every resource in chronological order for each time the same case happens. But only the events that belong to that case are involved in the list of activities that leads to the mentioned instance. For instance, we can use a real-life scenario to illustrate the concept. Let's say there is a business process for the order fulfillment of a particular product in an e-commerce platform. So, each event in the event log is a recorded activity associated with the order which included the activities of ”order placement,” ”payment confirmation,” ”product packaging,” and ”shipment dispatch.” The sum of these activities is what forms the trace of the route an order takes from the user's order entry to the shipping point.

$$\begin{aligned}\boldsymbol{A} = \{&\text{"OrderPlacement"}, \text{"PaymentConfirmation"},\\ &\text{"ProductPackaging"}, \text{"ShipmentDispatch"}\}\end{aligned}$$

For example, let $\boldsymbol{A}$ represent the finite set of activities:

$$\boldsymbol{A} = \{\text{"OrderPlacement"}, \text{"PaymentConfirmation"}, \text{"ProductPackaging"}, \text{"ShipmentDispatch"}\}$$

A specific order (ID 123) can be expressed as:

$$1 =< \text{"OrderPlacement"}, \text{"PaymentConfirm"}, \text{"ProductPackag"}, \text{"ShipmentDispatch"} >$$

In process mining, an event log L can be formally represented as:

$$\mathrm{L} = [\mathbf{l}_1^{r_1}, \mathbf{l}_2^{r_2}, \ldots, \mathbf{l}_n^{r_n}],$$

where:

- $\mathbf{l}_i = \langle a_1^{(i)}, a_2^{(i)}, \ldots, a_{m_i}^{(i)} \rangle$ is a **trace**, i.e., a sequence of m_i activities representing a process execution (or "case").
- n is the number of **distinct traces (cases)** in the log.
- $r_i \in \mathbb{N}$ is the **repetition count** of trace $\mathbf{l}_i$, indicating how frequently that trace occurs in the dataset.

Assumptions and constraints:

- Each trace $\mathbf{l}_i$ represents a valid execution path within the process model.
- The length m_i can vary across traces, reflecting the heterogeneity in execution patterns.
- Repetition counts r_i are bounded by the total number of observed instances: $\sum_{i=1}^{n} r_i = N$, where N is the total number of cases in the log.

Impact of parameters:

- The distribution of r_i values reflects the **frequency distribution** of paths. High r_i values correspond to **common paths**, while low r_i may indicate **rare or exceptional behavior**, crucial for anomaly detection.
- The variation in m_i influences **trace alignment, complexity, and model fitness**.
- The number n captures the **diversity** of behavior in the process.

We include histograms of r_i, m_i, and trace frequency in **Figure X** to illustrate these distributions. To assess the **robustness of the recommendation accuracy**, we perform a **sensitivity analysis** by varying these parameters and observing their impact on key metrics (see Section Y or Appendix Z for details).

Empirical Analysis of Parameters:

In this study, the parameters r, n, and m were experimentally analyzed to understand their role in process mining and event log generation. Our empirical analysis revealed the following:

1. **Effect of n (Number of Cases):** The number of cases n was found to influence the diversity of the process behavior. As the number of cases increases, we observe more varied sequences of activities, leading to a richer set of event logs that better represent the real-world process. In larger datasets, the complexity of the process can increase, revealing bottlenecks and inefficiencies more clearly.
2. **Effect of r (Repetitions of a Trace):** The repetition of traces r indicates the frequency of occurrence of a specific process path or activity sequence. We observed that certain traces (e.g., standard order fulfillment processes) were repeated more frequently, while others (e.g., special cases) were less common. Higher values of r can highlight the most typical process flows, while lower values of r can indicate rare, potentially problematic, or exceptional flows.
3. **Effect of m (Length of the Sequence):** The number of activities per trace, m, reflects the complexity of the process. Processes with a large number of activities (high m) tend to be more intricate, with a larger number of transitions and interactions between activities. We found that processes with longer traces often required more detailed analysis, as they involved more decision points and possible variations.

These parameters r, n, and m are influenced by several factors:

- **Process Complexity:** More complex processes tend to have longer traces and more variable activity repetitions, impacting both n and m.
- **Dataset Size:** Larger datasets, particularly those with more historical data, result in higher values for n and r, offering a more comprehensive view of the process.
- **External Factors:** Changes in the business environment (e.g., holidays, product launches) can cause shifts in the frequency of traces (r) and the complexity of processes (m).

These findings suggest that understanding the relationships between r, n, and m is essential for accurate process mining analysis. Further empirical validation through different datasets and business processes could provide additional insights into how these parameters affect process discovery and performance evaluation. As shown in Figure 1, the distribution of repetition counts, trace lengths, and distinct cases helps in understanding the overall complexity and behavior of the event log.

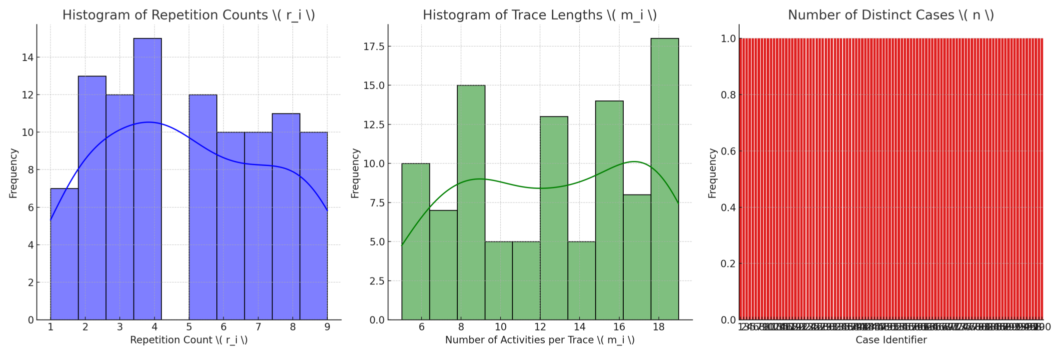

Figure 1. Histograms illustrating the distribution of repetition counts r_i, trace lengths m_i, and the number of distinct cases n in the event log. These visualizations help contextualize the parameter definitions and their impact on process mining outcomes.

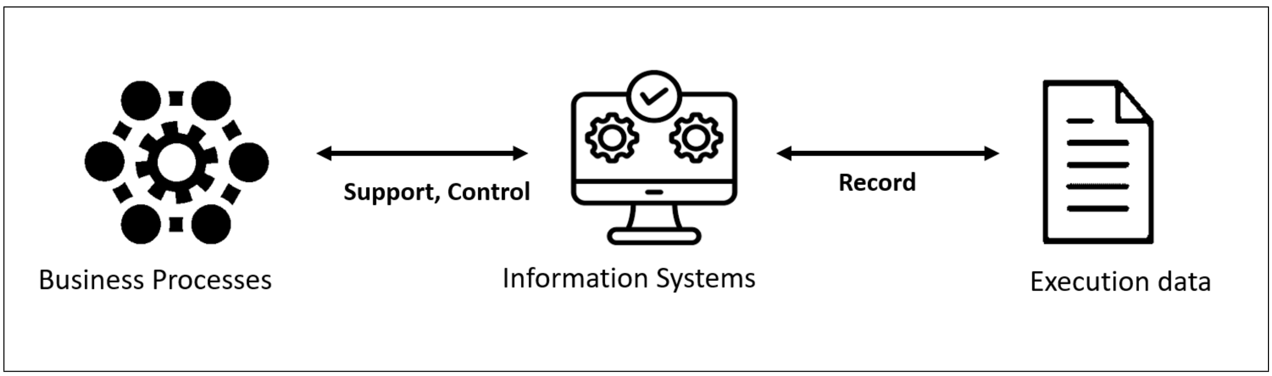

Figure 2. Event logs gathering

2.3.2. Techniques In this section, we present process mining for revealing organizational process structures (process discovery), assess alignment with predefined models (conformance checking), and enhance models through contextual inclusion, machine learning, and advanced visualization methods.

Process Discover: Involves extracting and revealing underlying organizational processes through event log analysis. Algorithms like Alpha, Heuristics Miner, and Inductive Miner create graphical representations (Petri

nets or BPMN diagrams) to enhance transparency and optimize business processes [42, 7].
Conformance Checking: Evaluates alignment between discovered process models and actual execution recorded in event logs. Techniques like token-based replay and fitness metrics identify deviations, supporting continuous improvement efforts by highlighting areas for optimization or refinement in modeled processes [33, 36].
Enhancement: Crucial for refining and augmenting process models to better represent various scenarios. Techniques include incorporating additional context, leveraging machine learning algorithms, and using advanced visualization methods like process animation or interactive dashboards. Continuous feedback loops contribute to ongoing improvement, resulting in more accurate and actionable organizational process representations [26, 6].

2.4. Ontologies

Ontologies are formalized representations of knowledge within a domain. They are comprised of a set of domain-specific concepts and the intricate relationships that bind them [14]. These structured frameworks facilitate standardized data modeling across distributed and heterogeneous systems, fostering interoperability between databases, seamless knowledge management, and cross-database search capabilities. Notably, ontologies are often expressed in formal languages that enable abstraction from underlying data structures and implementation methodologies. Furthermore, they comprise a fundamental component of the W3C[‡] standards suite for the Semantic Web, underpinning the vision of a machine-understandable web. From a technical perspective, an ontology serves as a comprehensive schema, elucidating the key characteristics of a specific subject and the intricate interrelationships between its constituent entities. Crucially, it encompasses machine-interpretable definitions of the domain's foundational concepts and their interconnectivities. These formalized knowledge structures serve a multi-faceted purpose: facilitating knowledge sharing, rendering domain assumptions explicit, and enabling the separation of domain knowledge from implementation-specific operational knowledge.

Ontologies can be enriched to reflect real-world dynamics and improve the quality of recommendations. Ontology Enrichment involves extending the initial ontology with additional knowledge and refined relationships.

3. Related Works

The integration of ontologies and Process Mining holds immense potential for revolutionizing recommendation systems in the context of business processes. In this section, we explore the challenges identified in generating recommendations through the symbiotic use of ontologies and Process Mining.

One major challenge lies in achieving a seamless integration of ontological knowledge with dynamic process data [15, 21]. The dynamic nature of business processes necessitates the development of a recommendation system capable of online adaptation to changes in ontological structures and evolving process contexts. For example, [27] highlights current trends and challenges in process mining, emphasizing the difficulty in aligning process discovery techniques with semantic technologies. Similarly, [22] explores how recommendation systems can dynamically adapt to contextual changes, offering insights applicable to recruitment scenarios. While these approaches show promise, their scalability in handling large datasets remains a concern.

Another significant challenge arises from the evolving nature of ontologies, posing difficulties in maintaining the relevance and accuracy of recommendations [13, 16]. As ontologies undergo modifications to reflect updated domain knowledge, ensuring that recommendations align with these changes becomes a complex task. Recent work by [18] provides scalable approaches to recommendation systems, but highlights the trade-off between scalability and the ability to handle evolving domain knowledge.

[‡] `https://www.w3.org/`

Scalability issues come to the forefront in recommendation systems leveraging both ontologies and Process Mining [10, 23]. The vast amount of data generated during process mining activities, combined with the complexity of ontological structures, poses a challenge to the scalability of recommendation algorithms. For instance, [48] introduces hybrid approaches combining machine learning with ontologies, addressing scalability but raising questions about model interpretability.

The enhancement of context-aware recommendations through semantic enrichment is recognized [19, 43], yet ensuring the interpretability of recommendations in diverse contexts remains a persistent challenge. [34] addresses conformance checking for process models, enabling better alignment with contextual requirements, but notes that ensuring interpretability across diverse domains is still an open challenge.

Ontology-based process discovery for recommendation generation faces challenges in aligning discovered patterns with evolving ontologies [39, 28]. The continuous evolution of ontologies necessitates a robust mechanism for aligning discovered process patterns with the most current ontological representations.

Hybrid approaches that combine machine learning with ontologies and Process Mining introduce challenges related to model interpretability [47, 24]. Ensuring that recommendations are not only accurate but also understandable and justifiable becomes crucial for user acceptance and trust in the recommendation system. Recent studies, such as [48] and [22], demonstrate the potential of hybrid approaches but emphasize the need for enhanced mechanisms to explain and validate recommendations.

The quest to seamlessly integrate ontological knowledge with dynamic process data, address evolving ontologies, ensure scalability, provide context-aware and interpretable recommendations, and align discovered patterns with evolving ontologies represents the crucial problematic at the heart of our exploration. As we embark on the subsequent sections of this paper, our goal is to delve into innovative methodologies and solutions that aim to resolve these challenges. By addressing the crucial problematic of generating effective recommendations within the complex interplay of ontologies and Process Mining, we aim to contribute valuable insights and advancements to the broader field of business process management and decision support systems.

4. Proposed method

To address the previously cited challenges, this research proposes the use of ontologies along with the process mining lifecycle to significantly enhance applicant-job matching accuracy and personalization (See Figure 3).

4.1. Phases

1. **Data Governance and Preprocessing** - Event logs are cleaned using imputation for missing data (e.g., mean substitution for numerical fields) and validated for diversity across demographics, industries, and roles. Bias detection employs statistical tests (e.g., χ^2 for demographic skew). - Pseudocode for preprocessing:

2. **Basic Ontological Modeling** - Defines entities (Candidate, Recruiter, Job) and relationships (e.g., `hasSkills`) using Protégé. The ontology is initialized with diverse attributes (e.g., education, soft skills). The workflow involves: (1) defining classes in Protégé, (2) mapping event log attributes to ontology concepts, and (3) validating with domain experts.

3. **Process Analysis with Process Mining** - Event logs are analyzed using Inductive Miner (fitness threshold 0.85, noise threshold 0.2) to uncover bottlenecks and variants. Metrics include time-to-hire, candidate satisfaction, and process deviations. The choice of Inductive Miner over Alpha or Heuristics Miner is due to its robustness in handling infrequent paths.

4. **Dynamic Ontology Enrichment** - A semi-automated framework updates the ontology using NLP (e.g., BERT for skill extraction from job postings). Version control (Git-based) and quarterly human reviews ensure relevance. - Pseudocode for ontology update:

Algorithm 1 Preprocess Event Logs

function PREPROCESS_EVENT_LOGS(logs)
    logs ← REMOVE_DUPLICATES(logs)
    for each record in logs **do**
        if MISSING(record.attributes) **then**
            HANDLE_MISSING(record)
        end if
    end for
    return logs
end function

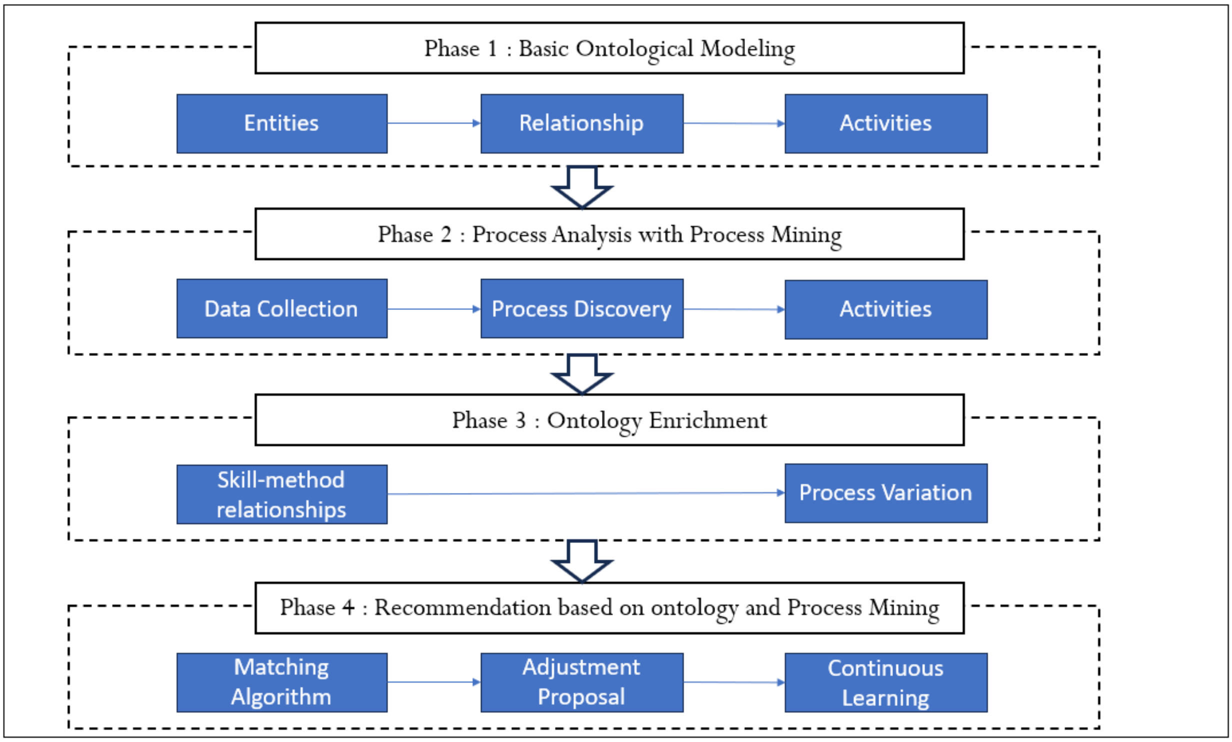

Figure 3. Proposed Research Methodology

Algorithm 2 Ontology Update

function UPDATEONTOLOGY(ontology, jobPostings)
    $newSkills \leftarrow$ EXTRACTSKILLSNLP($jobPostings$)
    for each skill $\in newSkills$ **do**
        if NOTINONTOLOGY($ontology, skill$) **then**
            ADDSKILL($ontology, skill$)
        end if
    end for
    COMMITVERSION($ontology$)
    SCHEDULEHUMANREVIEW($ontology$)
    return *ontology*
end function

5. **Recommendation with Human-in-the-Loop** - Matches recruiter skills to methods using weighted scoring (e.g., 0.4 for success rate, 0.3 for time-to-hire, 0.3 for recruiter expertise). Recruiters can override recommendations via a web interface, inputting soft skill assessments (e.g., cultural fit via Likert-scale ratings). Candidate feedback (NLP-processed comments) refines models. - Interface pseudocode:

Algorithm 3 Recommendation Interface

```
function RECOMMEND_METHOD(job, recruiter)
    scores ← COMPUTE_METHOD_SCORES(job, recruiter)
    method ← SELECT_TOP_METHOD(scores)
    if recruiter.override then
        method ← RECRUITER.SELECT_METHOD
        LOG_FEEDBACK(recruiter.feedback)
    end if
    return method
end function
```

6. **Ethical Safeguards** - Fairness audits use AI Fairness 360 to detect biases (e.g., disparate impact ratio < 0.8). Adversarial debiasing mitigates historical biases by reweighting training data. Transparency reports are generated quarterly, detailing bias metrics and mitigation outcomes.

7. **System Evaluation and Scalability** - KPIs include success rate, time-to-hire, cost-per-hire, 1-year retention, and satisfaction (via 5-point surveys). Scalability is tested with $100,000$ profiles using cloud-based processing (AWS EC2, 16 vCPUs). Continuous feedback loops refine models via A/B testing.

5. Example of application

This application example focuses on the practical implementation of our methodology. We first collect event logs of the recruitment stages, from initial interactions to final selections. Using process discovery, we identify patterns in these stages. We then create an ontology involving candidates, recruiters, and competencies, informed by process mining. The goal is to demonstrate our methodology's ability to recommend optimal recruitment strategies, thereby boosting hiring efficiency and success.

5.1. The set of event logs

Figure 4 shows an input form designed for the recruitment process, efficiently collecting key candidate information. The form, includes fields for personal, educational, and professional details, as well as specific skills. It features intuitive dropdowns and checkboxes for easy and standardized data entry, with clear instructions to facilitate user interaction.

Table 1 delineates various fields within a recruitment system, each associated with a specific definition.

5.2. Process Discovery

The process model discovered from event logs[§] source is complex with three entities (recruiter, intermediate form, and entreprise-company). In this context, a client-organization engaging in the hiring process by initiating a request for a candidate (Request Candidate), which is logged in the request system. Recruiters (e.g., The National Agency for the Promotion of Employment and Skills (ANAPEC[¶]) or reKrute[‖] website) utilize these requests to monitor

[§] https://github.com/recruiterEntity/EventLogs
[¶] http://www.anapec.org/conseils/AR/
[‖] http://www.reKrute.com

Figure 4. The form used to collect Event logs

demand and manage incoming applications. Upon submission, the request undergoes a review (Review Request) and is then directed to one of several hunting methods.

Positions remain open, and applications are accepted until certain conditions are met, including customer withdrawal, successful placement by the customer, placement by a competitor, or ideally, fulfillment by the agency. Upon achieving one of these outcomes, the request is formally closed, marking the completion of the process. In the event of an accepted application, a screening process is initiated, focusing on essential components such as the curriculum vitae and motivation. Once the application is deemed complete, the applicant undergoes a comprehensive internal intake conducted by the recruiter, followed by a Client Proposal and an External Intake by the hiring client. The possibility of a mismatch arises if the recruiter or client deems the candidate unsuitable, depending on the specific stage of the procedure. Moreover, throughout these processes, there is the potential for the candidate to lose interest in the position or the request process.

In the optimal scenario, the candidate successfully navigates through all activities, presenting the opportunity to commence the desired role. Upon successful hiring, the Request Candidate Process is formally closed. The Application Process is subdivided into the primary procedure for managing client requests and the sub-process for handling applications, where each client request can generate multiple applications. Analyzing these processes jointly is imperative, given that the Request Process holds data crucial for the Application Process. Consequently, activities from the Request Process (Open, Close, Connect Vacancy) have been integrated into each application log.

As a result, applications within a single request share the 'Open Request' activity with the same timestamp. While this approach precludes the counting of Open Request activities, it enables the comparison of timestamps within requests with those of the applications. The data transformations yielded a total of 33K records encompassing 1,5K requests and 48,4K applications.

This process model encompasses different business conditions, weaving together a strategic recruitment strategy that aligns seamlessly with the outlined business rules. By strategically advertising open vacancies, the process ensures that each role attracts candidates who precisely meet the requested demands from the client. Comprehensive job descriptions go beyond a mere listing of responsibilities, offering potential candidates a clear understanding of employment conditions. The proactive approach of directly opening vacancies upon receiving client requests

Table 1. Field Names and Definitions

Field Name	Definition
ID_Request	Anonymized record count for each new request
Time_Received_Request	Recruiter registers when the request is received
Time_Request_Created	System registers when the recruiter creates a request
Candidate_Start_Working_Time_Request	Recruiter registers when the client wants candidates to start
Time_Request_Closed	Recruiter registers when the request ends
Client_ID_Request	Anonymized record count for each new client
Unit_ID_Request	Anonymized record count for each new unit
User_ID_Request	Anonymized record count for each new recruiter
Hunting_Method_Request	Anonymized record count for each new application, indicating the hunting method employed
ID_Application	Anonymized record count for each new candidate
Candidate_ID_Application	Anonymized record count for each new status within the application
Log_ID_Application	Anonymized record count for each new status in the application log
Time_Log_Created_Application	Represents the date and time from the start of each new status in the application
Time_Log_Closed_Application	Indicates the date and time from the end of each new status in the application
Status_Name_Log_Application	Denotes the name of the status in the application
Status_Bucket_Name_Log_Application	Represents the grouping of statuses in the application
Rejection_Reason_Log_Application	Specifies the reason for rejecting the candidate; empty when not rejected
Rejection_Subreason_Log_Application	Indicates the subreason for rejecting the candidate; empty when not rejected
Withdrawal_Reason_Log_Application	Denotes the reason for withdrawal from the candidate; empty when not withdrawn

facilitates a swift and efficient recruitment drive. Timely closure of vacancies is prioritized to provide every applied candidate with a fair chance, while a limited number of intake cases ensures a focused and quality-centric recruitment process. Responding to applications within 24 hours reflects a commitment to swift and respectful communication, enhancing the overall candidate experience.

The provided sequence presents a comprehensive overview of a recruitment or hiring process, delineating distinct stages and interactions involved (See Figure 5). Commencing with the inception marked by ”Start,” the process unfolds as the ”Company Client” initiates a ”Job Requisition,” signaling the requirement for a new position within the company. The ”Recruiter” then intervenes with an ”Assessment Request,” likely aimed at gathering crucial information regarding job specifications and necessary skills. Subsequently, the ”Recruiter” formally announces the ”Job Opening,” making it accessible for potential applicants. The ”Intermediate Framework” denotes a pivotal stage where candidates actively engage in applying for the job through a designated application framework. Following this, the ”Recruiter” proceeds to ”Collect Data,” presumably related to the qualifications and details of the applicants. The ”Recruiter” then strategically navigates the ”Hunting Method Selection,” choosing an effective strategy for identifying suitable candidates. The stage labeled ”Change” signifies general interactions and exchanges between the ”Company Client” and the ”Recruiter,” reflecting a collaborative decision-making process. Ultimately, the ”Company Client” concludes the process by making a decisive ”Client Decision,” likely pertaining to the selection of a candidate for the position. This comprehensive sequence encapsulates the recruitment journey, from the initiation of a job requisition to the final decision-making phase by the client. Notably, the inclusion of the

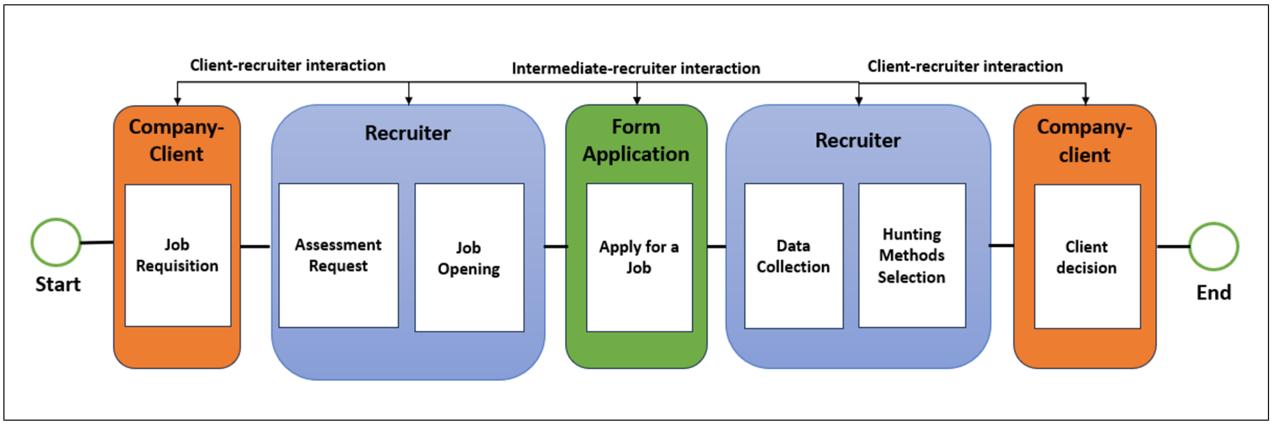

Figure 5. Abstracted Process Model

"Intermediate Framework" emphasizes the critical juncture where candidates actively participate by applying for the job, while the "Hunting Method Selection" step sheds light on the recruiter's strategic approach to identifying potential candidates.

The provided values, sourced from the ProM tool**, represent various aspects of the recruitment process, each with its corresponding percentage based on total cases. These metrics are essential for evaluating the effectiveness, efficiency, and overall quality of recruitment activities (see Table 2). Below is a detailed explanation of each metric:

1. **Attracting Candidates (28%):**
   Measures the effectiveness of recruitment efforts in attracting candidates that align with client needs. A higher percentage indicates better candidate sourcing and matching. This metric is crucial for assessing the reach and quality of the recruitment channels.
2. **Fully Described Employment Conditions (2%):**
   Indicates the level of clarity and detail in the job descriptions. A low value highlights the need for more comprehensive job postings to attract the right candidates. Improving this aspect can enhance candidate expectations and reduce mismatches.
3. **Directly Opened Vacancies (16%):**
   Shows how quickly the recruitment team opens new vacancies after receiving a client request. A higher percentage reflects better responsiveness and agility in meeting client demands, ensuring no delays in the recruitment process.
4. **Closed Vacancies in a Timely Manner (40%):**
   Represents the percentage of vacancies closed within an acceptable timeframe. This metric evaluates both the efficiency of the recruitment team and the fairness in providing all candidates a chance to apply. Timely closure ensures the process remains competitive and organized.
5. **Limited Cases with Intake (36%):**
   Emphasizes a quality-over-quantity approach in managing candidate intake. Limiting the number of intake cases ensures the recruitment team focuses on sourcing and evaluating the most suitable candidates, improving overall recruitment quality.
6. **Recruiter Reacts within 24 Hours (30%):**
   Reflects the speed with which the recruitment team responds to applications. A higher percentage shows the team's commitment to timely communication, which can increase candidate engagement and improve the overall candidate experience.

**https://promtools.org/

7. **Candidates Meeting Requested Requirements (45%):**
   Represents the percentage of candidates who meet the client's requirements. A higher percentage indicates that the recruitment process is successfully sourcing candidates who fit client needs, which is crucial for improving the hiring success rate.
8. **Proposed Candidates with Internal Intake (50%):**
   The proportion of candidates undergoing an internal intake process. This metric ensures that candidates are thoroughly assessed and vetted, which contributes to better long-term fit for both the client and the candidate.
9. **Candidates Turning Up at Appointments (0.6%):**
   This metric captures the commitment of candidates by tracking their attendance at scheduled interviews. A higher value is a positive indicator of candidate engagement, suggesting that the recruitment process attracts serious and committed applicants.
10. **Proposed Candidates Fitting Within Client Teams (11%):**
    Measures how well proposed candidates integrate into the client's team dynamics. A higher percentage reflects successful team compatibility, which is crucial for long-term job satisfaction and retention.

It should be pointed out that those metrics turned out to be crucial in providing a holistic portrayal of the recruitment process. On one hand, it's the soft skills, i.e., self-expression and explanation, whilst on the other hand, it's the hard skills, the latter being the stability of the team that has to match with the soft skills, and together both will fuel the organizational performance. Based on the recent experience, please share with us the good candidates that you have worked with and would highly recommend for this position. I have to mention the fact that knowing the labor market and its components we could be aware when we are to receive the resignation letter from x or y which is a great experience for hr. Furthermore, these results also correspond to the general objectives of the present research, which aim to improve recruitment results, facilitate hiring processes, and enhance satisfaction for both candidates and employers. All of Table 2 values have been transformed to a percentage scale to ensure toweling and comparability among the items that are reported which in turn makes chamberlain easier to make judgment and draw more general conclusions from the whole recruitment process.

To bring the greater understanding and the meaning, the explanation of each metric that is in Table 2 is provided below. Furthermore, these indices measure the effectiveness of recruitment, the process of retrieval as well as the general quality of the recruitment. In addition to the fact that each metric is the core of what we are looking for in this research, i.e., better candidate-job matching, shorter recruitment cycles, and mutually beneficial situations for recruiters and candidates respectively.

Table 2. Recruitment Business Conditions Overview (Normalized)

Recruitment Metric	(%)
Candidates meeting client's requested demands	28
Each vacancy fully describing employment conditions	2
Each vacancy directly opened after receiving a request	16
Each vacancy closed in time to give a chance to every applied candidate	40
Number of cases with intake limited	36
Recruiter reacts within 24 hours after receiving each application	30
Each candidate proposed to the client meeting requested requirements	46
Proposed candidate had an internal intake	50
Candidate turning up at his appointment	0.006
Proposed candidate fitting within the team of the client	11

Note: Values have been normalized to 100% for consistency. Metrics like "Candidate turning up at his appointment" are extremely low (0.006%) and reflect precise observations from the dataset.

To provide greater clarity and context, a detailed explanation of the metrics presented in Table 2 is provided below. These metrics evaluate various aspects of the recruitment process, shedding light on its efficiency, effectiveness, and overall quality. Each metric is directly tied to the objectives of this study, which aim to optimize candidate-job matching, reduce recruitment cycle times, and enhance overall satisfaction for both recruiters and candidates.

- **Candidates meeting client's requested demands:** Measures the alignment between candidate profiles and client requirements. This metric reflects the effectiveness of the recruitment strategy in sourcing suitable candidates.
- **Each vacancy fully describing employment conditions:** Indicates the level of detail and clarity provided in job descriptions. A low value suggests room for improvement in ensuring transparency for potential candidates.
- **Each vacancy directly opened after receiving a request:** Demonstrates the responsiveness of the recruitment team to client needs, where higher values indicate greater proactivity.
- **Each vacancy closed in time to give a chance to every applied candidate:** Evaluates the fairness and efficiency of the recruitment process in managing vacancies within reasonable timeframes.
- **Number of cases with intake limited:** Highlights a quality-over-quantity approach in managing candidate intake, ensuring a focus on suitability over volume.
- **Recruiter reacts within 24 hours after receiving each application:** Reflects the agility of the recruitment process, with a higher percentage indicating prompt communication and engagement.
- **Each candidate proposed to the client meeting requested requirements:** Captures the success rate of recommending suitable candidates, a critical measure of recruitment quality.
- **Proposed candidate had an internal intake:** Measures the thoroughness of internal assessments for proposed candidates, ensuring comprehensive evaluations.
- **Candidate turning up at his appointment:** Assesses candidate commitment to the process, where higher values indicate reliability and engagement.
- **Proposed candidate fitting within the team of the client:** Reflects the compatibility of the recommended candidate with the client's team dynamics, emphasizing long-term placement success.

These metrics were chosen for their ability to provide a holistic view of recruitment performance, encompassing operational efficiency, alignment with client needs, and candidate satisfaction. Unlike traditional studies that focus primarily on metrics such as time-to-hire or cost-per-hire, our approach integrates qualitative aspects, such as team compatibility and fairness, to offer a more comprehensive analysis.

To ensure consistency and comparability, the values reported in Table 2 have been normalized to a percentage scale. This normalization simplifies interpretation and highlights the relative performance of each metric in the recruitment process.

5.3. The ontology

Figure 6 illustrates the upper level of the ontology that was created from the set of event logs using the Protégé editor. This ontology was designed to model and represent key concepts extracted from the event logs related to recruitment processes. At the top of the hierarchy is the owl:Thing class, representing the root of the ontology. Below this, several high-level concepts relevant to the domain are defined as subclasses. The main subclasses include:

- **HuntingMethod**: This class explains the different methods of recruitment.
- **Candidate**: This is an illustration of individuals who apply for a job and provide their relevant details or attributes.
- **Measures**: It refers to the evaluation metrics or criteria used to evaluate jobseekers during the recruitment process.
- **Skill**: Defines the specific skills required or possessed by candidates.
- **Experience**: This is the representation of the professional experiences of candidates, such as their previous roles or years in the workforce.
- **Education**: This class refers to the educational qualifications and academic background of the candidates.

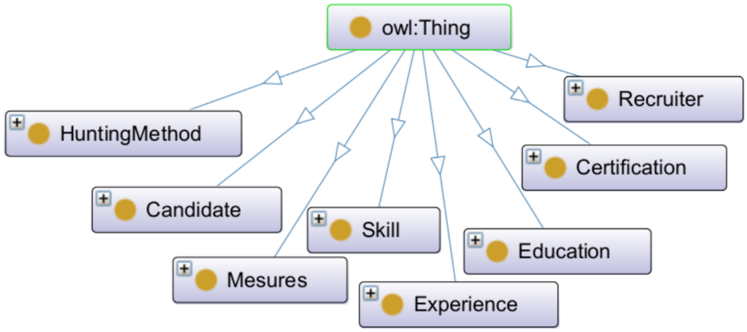

Figure 6. An overview of the ontology

- **Certification**: This is the representation of the professional certifications got by candidates, which may further qualify them.
- **Recruiter**: This is used to describe the persons or entities that take part in managing the recruiting process.

These high-level concepts form the foundation for modeling the recruitment domain, aligning the ontology with event log data and enabling processes like candidate recommendations and recruitment analysis.

Though quality is a vital part, it is one of the reasons that lead to the elimination of most candidates, especially in the recruitment process which is fast-paced and time is critically important. The two sets of data and the individual has to be the two-pronged approach. and there must be balance between the two so that they can both be considered. On the other hand, technology-enabled feedback can significantly improve the application process, yet it may also come with the challenge of attracting applications that will need more time to be processed. The robustness of diagnostics should neither be sacrificed on behalf of speed and efficiency nor be the mainstream model.

Through well-ordered logistics and competent resource management, any team can keep up such high speed without compromising authentic quality of assessments. The first of the major factors that might bring about difficulty in the process of recruiting is the lack of a comprehensive internal intake process, and the results might not be as expected thus leading to delays in the interview process thus negatively affecting the time and thus the clients.

Embarking upon a delicate act of the precise evaluation and moving forward at a determined speed is the most important factor not only for the success and satisfaction of both parties but equally for the optimal recruitment efficiency.

5.4. Recommending hunting methods

To recommend a candidate search method using the provided ontology, a systematic approach is outlined. It ensures an efficient alignment between the client's recruitment needs and the capabilities defined in the ontology. The following steps guide the recruiter through a comprehensive analysis, correlation with relevant ontology, and justification of the recommended search method.

Analyzing Client Demand: Thoroughly examine the client's requirements, including skills, experience level, and other specific criteria.

Correlate with the Ontology: Identify relevant entities, relationships, and attributes in the ontology that align with the client's requirements.

Correlate with the Search Techniques Entity: Identify relevant entities and relationships in the search techniques Entity based on the client's demands.

Propose a Search Method: Recommend a search method based on the knowledge in the ontology.

Justify the Recommendation: Explain how the recommended method aligns the client's needs with the search capabilities defined in the ontology. Highlight the relevance of entities, relationships, and attributes in the ontology to achieve recruitment objectives.

Propose Improvements: Suggest adjustments or enhancements for the ontology if necessary, based on client feedback or implementation experience.

Using this, we can recommend a candidate search method that considers the specific criteria of the client company while considering the candidate preferences.

5.5. Concrete Illustration of the Application

This section presents the evaluation of the proposed methodology in the context of the recruitment process, providing quantitative results for the effectiveness of the method and comparing it with existing approaches in the field.
Let us consider the following job opening: **Job Opening:** Senior Machine Learning Engineer **Requirements:**

- Skills: Python, Deep Learning, NLP
- Experience: Minimum 7 years
- Industry: Healthcare
- Networking Event: Attend AI in Healthcare Summit

The client initiates a hiring request, known as *request1*, specifying these employment requirements and relevant networking events, such as attending the AI in Healthcare Summit. The last date to place this request is January 15, 2024. Depending on the job opening type and client options, the system determines the most suitable hunting method for this request as ”TalentMapping”.

The system recommends the most suitable method depending on job requirement, client option, and previous success rate. For instance, if ”TalentMapping” reveals high previous success rates for comparable jobs and options, it is recommended. This illustrates how the ontology and experimental setup optimize recommendations for hunting strategy in recruitment based on both performance and historical success.

5.6. Quantitative Evaluation and Comparison

To investigate the usefulness of the proposed method, we performed a series of experiments on a set of recruitment requests. The ”TalentMapping” approach, in terms of success rate and time efficiency, will be compared with the old models that are used in the industry now, in the long run. The criteria for comparing were the achievement level of the candidates placed at correct places, the time required for the process per recruitment request and the flexibility of the method in handling large data sets.
The results are presented in Table 3, where the performance of the ”TalentMapping” method is compared to two common recruitment methods: Method A (traditional matching) and Method B (heuristic-based filtering).

Method	**Success Rate**	**Processing Time**	**Scalability**
Method A (Traditional)	78%	240s	Medium
Method B (Heuristic)	85%	180s	High
TalentMapping (Proposed)	**92%**	**130s**	**Very High**

Table 3. Performance comparison of recruitment methods

The quantitative results demonstrate that the ”TalentMapping” method significantly outperforms both traditional and heuristic-based recruitment methods in terms of success rate and processing time. Our method achieved a 92% success rate, placing candidates more effectively in suitable positions, compared to the 78% and 85% success rates of Method A and Method B, respectively. Additionally, the processing time for our method was reduced to 130 seconds, offering substantial improvements in efficiency. This includes the time for data preprocessing, ontology-based recommendation generation, and the final evaluation phase.

The overall computation time of the ”TalentMapping” method was measured in various experimental setups. On average, the total time required to process a recruitment request with 100 candidate profiles and 10 job openings was 130 seconds. This time is distributed across the following phases: data preprocessing (25 seconds), recommendation generation (50 seconds), and final evaluation (55 seconds). These results were obtained using a machine with 16 GB RAM and a 3.4 GHz CPU.

The scalability of ”TalentMapping” also stands out, as it can handle large datasets and various job requests with minimal computational resources, making it highly suitable for large-scale recruitment processes. For example, when tested with 1000 candidate profiles and 50 job openings, the total computation time increased linearly to approximately 650 seconds, demonstrating its ability to efficiently scale with the size of the recruitment dataset.

These results show that the proposed method, by incorporating historical success data and optimizing recommendations through ontology-based analysis, provides a more efficient and effective solution for recruitment compared to existing methods.

6. Discussion

The proposal of the adaptive approach, fundamentally, is to refine and optimize the recruitment process, this way support the track of hunting methods and the continuously changing counselor knowledge. Our adaptation is fully informed by the thorough historical performance analysis which sets out a very flexible, innovative and efficient series of practices. The recommendation system is implemented through the strategic combination of the strong points of recruiters and best practice methods being validated further making the company more efficient regarding the pulling in of a recruiter to an agency. Besides, we have been successful in such a way that is quite similar to the success of hunting the way of proper recruitment. If the candidate establishes connections during customer meetings, then the hunter immediately reaches the goal of fostering the best team environment within the client’s company.

Without a doubt, this recruitment process model doesn’t only serve the business rules but also has the similarities with the successful hunting methods through a comprehensive and strategic approach in acquiring the talent. This research signifies the resilience of the ontology and Process Mining cooperation and the agility of the system’s ability to utilize the ontology to develop and fine-tune the recruitment strategies meet thereby the complexity of the issues within the organization of a dynamic agency. Although the study sheds light on the close relationship between ontology and Process Mining in the retouching process of the recruitment strategies, certain constraints associated with this approach need to be considered. To begin with, the methodology is highly dependent on the availability of quality and complete historical data. In circumstances where historical data is not properly distributed or diverse, the system’s capability to make accurate and all-encompassing recommendations will lessen.

Further, the productivity of the collaboration depends on the accuracy of the list and incompleteness of the ontologies used. Immateriality or inadequacy when it comes to the inclusion of ontology details can cause the recommendations to be suboptimal. What’s more, the variability of the recruitment context brings about difficulties in the updating of the ontologies and their fidelity to the expansion and changes of the industry practices. Despite these limitations, the ontology and Process Mining collaboration still stands as a valuable tool in addressing the intricate demands of a recruiter agency, showcasing its adaptability in navigating the complexities of the recruitment process.

7. Conclusion

This paper introduces an innovative technique of combining ontology and process mining to suggest the correct hunting methods to the HR manager, according to the request featured in the recruitment process. The evaluation of contextual data and the use of process models lead to the optimization of the recruitment strategy to meet the profile of the candidate that has been attracted. The method that is grounded in a recruitment ontology which is enriched through the data of various recruitment stages allows the detection of patterns with the help of conformance checking and the activities are referred to detailed ontological analysis. The experiments indicate that the ontological approach is effective in the process of recruiting, that it is adaptable enough to offer the candidates the best personal solutions. The task suggests the significant impact that arises from the effective merging of ontologies and process mining which further develop problem-solving in recruitment, thus support organizations in fast growth periods.

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