DOI: 10.2507/35th.daaam.proceedings.xxx

HR-TECH AUTOMATION: A CASE STUDY OF RESUME DESIGN USING GENAI TECHNOLOGIES

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This Publication has to be referred as: Suleykin, A[lexander]; Babenko R[oman]; Panfilov, P[eter] (2024). HR-Tech Automation: A Case Study for Resume Design using GenAI Technologies. Proceedings of the 35th DAAAM International Symposium, pp.xxxx-xxxx, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3-902734-xx-x, ISSN 1726-9679, Vienna, Austria
DOI: 10.2507/35th.daaam.proceedings.xxx

Abstract

With the development of technologies and the increase in the amount of data that companies work with, the use of large language models (LLM) is becoming an integral part of modern business processes. These models not only demonstrate impressive results in natural language processing, but also open up new horizons for automating routine tasks. In particular, in the field of HR-Tech, LLMs can significantly simplify the processes associated with resume processing, which makes them especially relevant for companies seeking to improve the efficiency of their HR departments working with a large amount of text data and resumes of candidates engaged in outstaffing both on the side of customers and contractors.

Keywords: Artificial intelligence, Generative AI, LLM, HR-automation.

1. Introduction

HR technology automation plays a key role in modern HR management, especially in the context of processing large amounts of data and increasing the efficiency of recruiting processes. One of the key aspects of automation is the processing of candidates' resumes, which includes their formatting and analysis for the subsequent selection of the most suitable specialists.

With the development of artificial intelligence (AI) and machine learning (ML) technologies, it has become possible to use these tools to automate the resume formatting process. Generative AI technology (GenAI) is one of the most promising areas in the field of HR automation, which can significantly increase the efficiency of HR specialists.

The purpose of this article is to conduct a case study on the use of GenAI technologies to automate the resume formatting process. We will consider how these technologies can be used to speed up the process of CV formatting of random candidates to one specific unified format, improve the quality of resumes, speed up the process of their analysis and decision-making on candidate selection. In this paper, we consider different aspects of HR-processes automation using GenAI technologies, review difficulties of CV-formatting process, propose component architecture and Use Cases diagram, compare different open-source LLM-models, describe different data extraction pipeline options and give an estimation accuracy example. In addition, future work and other promising tasks in HR-tech industry with Gen AI technologies are described.

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2. Literature review

Large Language Models (LLMs) are increasingly being utilized in Human Resources (HR) to streamline various processes, enhancing efficiency and effectiveness. Their applications range from automating resume screening to developing conversational agents for employee inquiries. Notably, the HR-MultiWOZ dataset provides a foundational resource for training LLMs in HR-specific dialogues, addressing privacy concerns while facilitating data generation (Xu et al., 2024). Additionally, LLMs have shown promise in automating repetitive tasks, such as handling time-off requests and medical claims (Afzal et al., 2024). Furthermore, LLMs can serve as zero-shot human models, improving interactions in HR-related scenarios by understanding context and planning responses ("Large Language Models as Zero-Shot Human Models for Human-Robot Interaction", 2023). Overall, the integration of LLMs in HR represents a significant advancement in optimizing workflows and enhancing employee engagement.

However, challenges remain, including the need for high-quality training data and the potential for biases in automated decision-making processes, which could impact fairness in HR practices (Zhang et al., 2023)(Salakar et al., 2023). Large Language Models (LLMs) are revolutionizing CV formatting and resume screening by enhancing the automation and efficiency of these processes. LLMs can effectively analyze unstructured data from resumes, capturing nuanced information that traditional methods often overlook. This capability is particularly beneficial in recruitment, where LLMs can summarize, grade, and even assist in decision-making regarding candidate selection. Key aspects include:

- **Enhanced Resume Screening.** LLMs automate the screening process, making it 11 times faster than manual methods (Gan et al., 2024). They improve the F1 score in resume classification, achieving 87.73% accuracy (Gan et al., 2024).
- **Multi-modal Understanding.** LLMs can integrate textual and visual data, enhancing the quality of CVs by generating descriptive content from images (Ma et al., 2024). This multi-modal capability allows for richer, more informative resumes that stand out to recruiters.
- **Addressing Unstructured Data.** LLMs excel at converting unstructured data into structured formats, ensuring critical information is not lost (Ghosh & Sadaphal, 2023).

While LLMs present significant advantages in CV formatting and recruitment, concerns about bias and transparency in automated systems remain critical issues that need addressing to ensure fair outcomes in hiring processes.

To sum it up, reviewed papers consider different HR-aspects automation, but there is no resume-formatting cases described in a detailed fashion. Thus, the novelty of the proposed paper focuses on the detailed resume-formatting Use Case based on different and most-advanced open-source LLMs. The paper provides a deep-dive into the process of converting CV of a random candidate to one specific unified format, describing architecture of proposed solution, difficulties, different techniques of interacting with LLM and the benchmarks, as well as the estimation of proposed solution and business value.

3. LLM for HR-Tech: Opportunities and prospects for use

LLMs open up a whole range of opportunities for HR specialists, allowing them to automate routine operations and improve work efficiency. For example, LLMs can:

- **Format resumes:** bring resumes to a single standard, which greatly simplifies their analysis and comparison;
- **Match candidates with vacancies:** analyze resumes and job requirements, identifying the most suitable candidates;
- **Generate Job Descriptions:** Create attractive and informative job descriptions that will be of interest to potential employees.

Automating such tasks with LM allows HR specialists to focus on more strategic issues such as talent selection, candidate interviews, optimization of internal HR processes and employee development.

A. The main difficulties of developing an AI-assistant for HR

Despite the promising prospects, the development of an AI-assistant faces a number of difficulties:

- **The specifics of HR cases:** the HR field requires a special approach that takes into account the variety of resume formats, the difference in the structure of resume writing among candidates and professional skills, which creates additional difficulties in the development;
- **Hallucinations:** LLMs can generate non-existent or implausible information, which can lead to errors in the selection of candidates or erroneous interpretation of candidates as not suitable for a specific vacancy;
- **The need to integrate external data and their constant relevance.** To achieve high results, integration with various systems and databases is required, which can be technically, financially and organizationally difficult. Additionally, it is necessary to ensure regular uninterrupted data updates, as the candidate database is constantly becoming outdated and not relevant.

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4. Case Study: Automation of resume formatting

Our team was working on a project for a small IT company, the purpose of which was to speed up the resume processing process. At the entrance, we received resumes in various formats that needed standardization, and at the exit we received documents ready for consideration with a single structure and design.

4.1. Task description

It is necessary to process resume files automatically according to the specified template and requirements for structuring and formatting the text. The sources come in the following formats:

- .rtf format always looks the same,
- .doc/.docx - may look different,
- .pdf - always look different.

First name S.

Job title

Female – ж / Male - м, X years
Location: X city

Hard skills:

X, X1, X2

Experience — _ years _ months

The month and year of the start of work — The month and year of completion of work or present time	Job title - Duty 1; - Duty 2 etc.

Education:

- 20__, IHE
Faculty, specialty
- 20__, IHE
Faculty, specialty

About myself:

About myself; courses

Fig. 1. An example of a corporate template for structuring a resume

Additional requirements for the content of the converted resume:

- The resume must match the template, starting from the most recent experience to the very first (sometimes resumes are thrown off, where on the contrary people indicate the experience of old years first, and only the last one at the end);
- The functions performed must be written in a list, while in each sentence the subjects must be predicates (for example: “Module development...");
- The resume should not contain the names of companies and projects (it is necessary to depersonalize);
- The stack should not contain, for example, "English", etc., but only technologies;
- The point about education adapts to the candidate - not everyone has a higher education, when it is not necessary to remove the word "Higher" and leave just "Education". In the same place, if there are several of them - from the last to the old (year, name of the university/ college, etc., faculty and direction);
- If the resume contains completed courses and advanced training, this is indicated in the "About me" section.

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4.2. Solution architecture

We have chosen DUC SmartSearch platform as the main platform for implementing the solution, as it was ideally suited for our task with minimal modifications. DUC SmartSearch is a digital ecosystem of AI assistants, its fork of the Danswer open-source system, which allows us to create add-ons on various LLM models, both proprietary (GigaChat, YandexGPT, ChatGPT, etc.) and Open-Source (LLAMA, GEMMA, etc.). A visual node pipeline editor has been added to the system, where you can independently create new individual LLM and AI agent orchestration pipelines for any subject area in low-code mode. The conceptual architecture of the solution is the following:

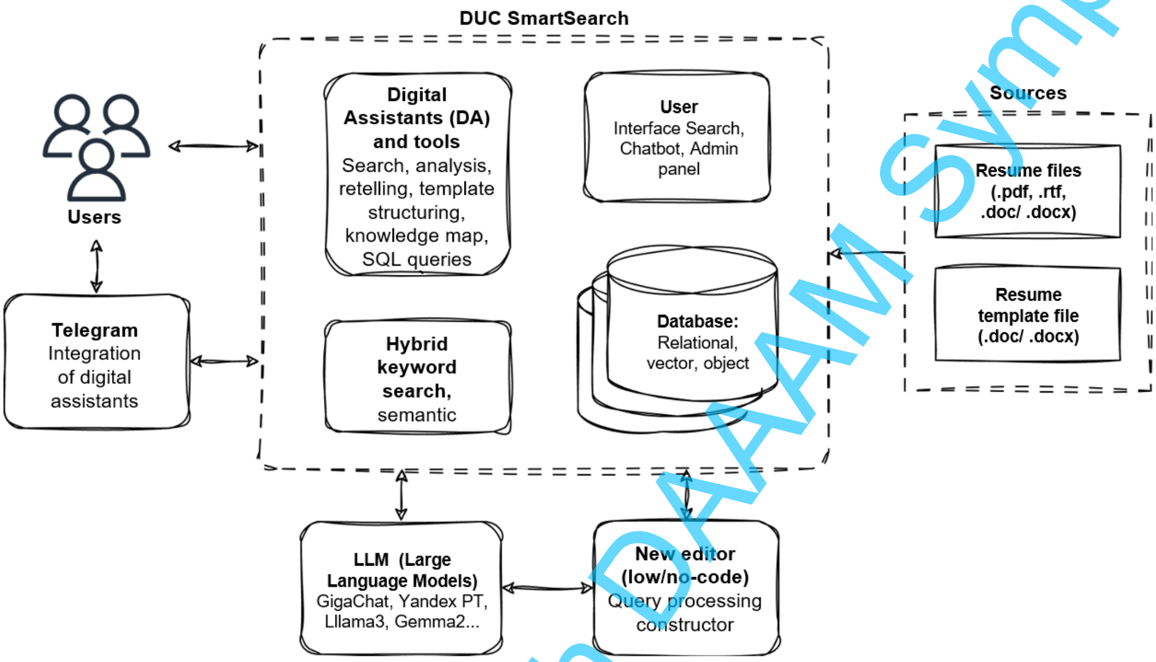

Fig. 2. A conceptual architecture of the resume formatting case implementation on the DUC SmartSearch platform

An additional digital assistant «HR assistant» was created in the system, and a special tool was developed and added - ResumeTool. This tool allows the digital assistant to work with files: upload the original resume, send it to the processing pipeline, fill in the template file with extracted data and save the formatted resume in the object storage. Users with the administrator role can upload their resume template or other documents in the tool settings.

The following figure shows a diagram of the use cases of the developed resume formatting solution.

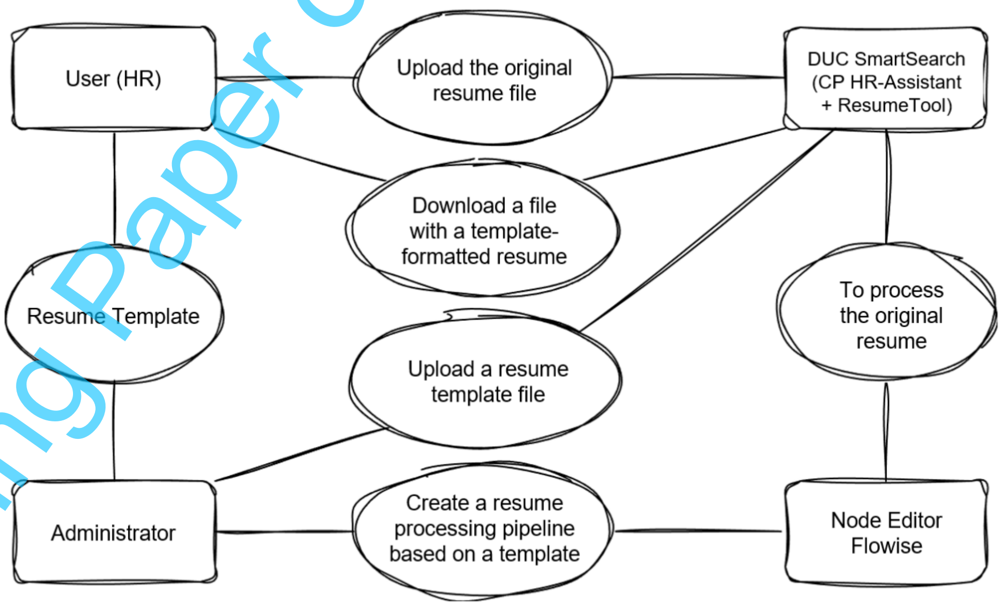

Fig. 3. Resume structuring according to a given template in DUC SmartSearch (use cases diagram)

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5. Results: Smart Assistant for resume formatting

5.1. Resume processing in the DUC SmartSearch platform

The resume processing algorithm in the DUC SmartSearch system is as follows:

1. The administrator downloads the necessary resume template file on the settings page of the ResumeTool digital assistant "HR Assistant" tool;
2. Then the administrator sets up the pipeline for processing the initial resumes in the Flowise node editor (the stage of implementation and initial configuration of the system);
3. To process resume files according to a given template, an ordinary user goes to the "Chatbot" page, selects the configured digital assistant "HR assistant" and uploads the resume file for processing;
4. When the user sends a resume file on the Chatbot page, it is forwarded to the Flowise pipeline prepared, processed and the structured text of the resume is returned to the digital assistant. Next, the received text is processed into a specified template and the user is provided with a link to download the prepared file. The interface of the system is as follows:

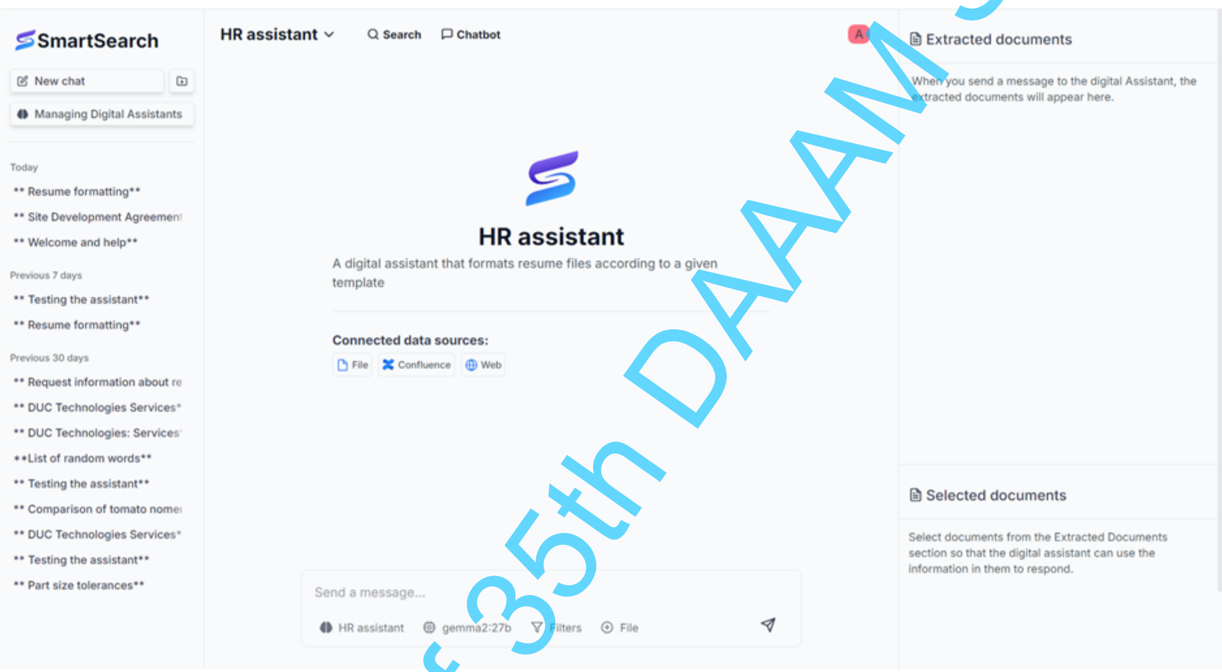

Fig. 4. Interface of the DUC SmartSearch Chatbot page

5.2. The development of the resume formatting pipeline

The solution for formatting the resume text was based on a data extraction approach similar to drawing up a Knowledge Maps – the approach, when all text is divided into N-topics, and for each topic a specific questions and typical answers are listed.

The main idea is to extract information in JSON format from unstructured data using LLM. During the development process, three pipeline schemes for information extraction were tested (Fig. 5):

In the first iteration of the developed pipeline, one common prompt was used to obtain information on all sections of the resume. The approach showed poor quality of the result - skipping data, ignoring instructions, and a high level of hallucinations (inventing). We believe that it is still difficult for language models to fulfill many text analysis requirements in a single query.

The second iteration of the pipeline was based on filling in the entire JSON structure at the first request and subsequent requeries to check and edit individual fields in the general JSON. The processing results became much better, and the solution was passed on to HR specialists for testing. After processing a couple of dozen resumes, shortcomings were identified, some of which were eliminated by tuning prompts.

Switching to the third version of the pipeline made it possible to eliminate the remaining comments, and also made it possible to flexibly configure each section individually. At the same time, the number of tokens transferred increased, since the entire text of the original summary was transferred to the model to extract each JSON field. This was not critical for us, because it did not significantly affect the processing speed, and the inference of the model was carried out locally on the GPU (without paying for tokens). In this project, the quality and stability of the processing result were prioritized over other non-functional requirements.

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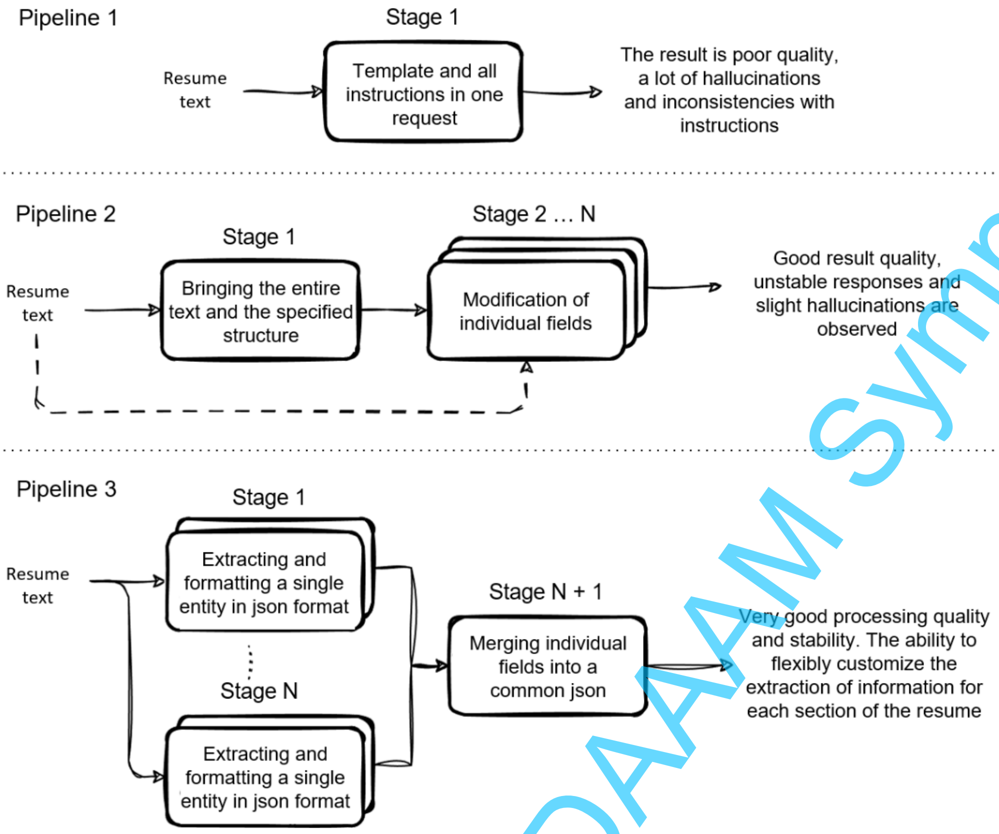
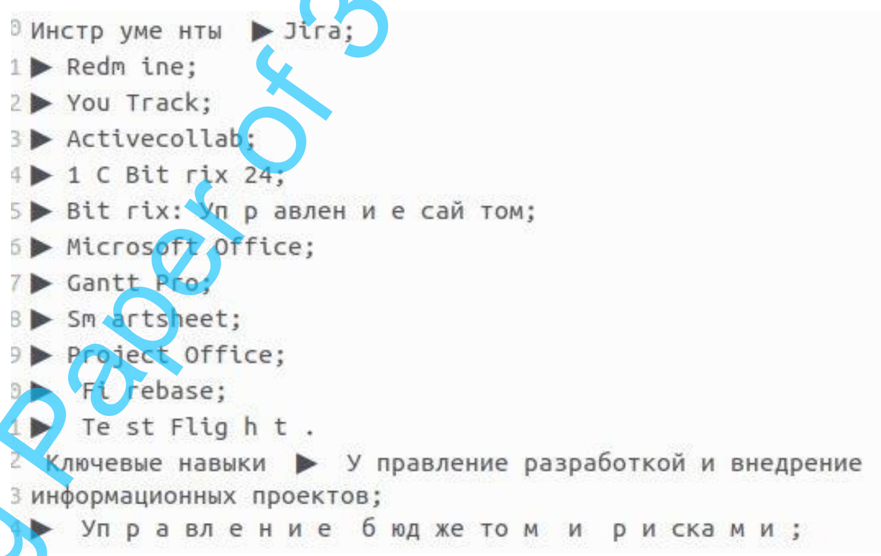


Fig. 5. Options for data extraction pipelines

5.3. Other tasks to be solved during the development process

Some .pdf summaries have a problem with incorrect encoding - when parsing text between letters in words, extra spaces appear. Such a "leaky" LLM text is very poorly processed or not processed at all:



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Инстр уме нты  ▶ Jira;
▶ Redm ine;
▶ You Track;
▶ Activecollab;
▶ 1 C Bit rix 24;
▶ Bit rix: Уп р авлен и е сай том;
▶ Microsoft Office;
▶ Gantt Pro;
▶ Sm artsheet;
▶ Project Office;
▶  Fi rebase;
▶  Te st Flig h t .
 Ключевые навыки  ▶  У правление разработкой и внедрение
информационных проектов;
▶  Уп р а вл е н и е  б юд же то м  и  р и ска м и ;
```

Fig. 6. A fragment of the problematic text

Based on the results of experiments with flavors and various models, the following solution was found. At the beginning, we count the number of spaces in the text and calculate their percentage to the total number of characters in the text. If it is greater than some average value for normal resume texts, then remove all single spaces. This prepared text is sent to the preliminary pipeline, in which the model places the missing spaces. It does a good job with this task, unlike removing unnecessary spaces between letters in words. Next, the resulting text is processed according to the main pipeline.

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6. Discussion

7.1. Project results

After the introduction of automation, the time for resume formatting was reduced by 6 times. The following shows how much time was spent on formatting before and after using the AI Assistant:

- Before automation: an average of 30 minutes for formatting one resume by an HR employee.
- After automation: 2 minutes for automatic formatting and 3 minutes for verification, a total of 5 minutes.

Taking into account the processing of an average of 100 resumes per month by one HR specialist, the implementation of this solution has made significant time savings (more than 40 hours of HR specialist work per month).

Looking ahead, we note that the final solution works on the multilingual Gemma 2 27B model with Q4 quantization. These parameters allow us to run the model on a user segment video card with 24 GB of video memory.

7.2. Evaluation of results

As an alternative, we tested three more open-source local large language models: Mistral NeMo 12B Q8, Llama 3.1 8B FP16, Saiga-llama3 8B FP16. The quality of their processing turned out to be an order of magnitude worse than that of the selected model - inventing information, adding unspecified json fields, looping response generation, etc.

To evaluate the results of resume processing using the selected model, a testing methodology based on processing 10 random resumes with subsequent evaluation by three independent experts was applied. Points were awarded based on the quality of filling in each section of the resume separately on a 5-point scale:

1 - Fictional Information Is Present;
2 - The Information Was In The Text, But Was Not Extracted;
3 - Only Part Of The Information Has Been Extracted;
4 - All Information Has Been Extracted, But Formatting Requirements Have Not Been Met;
5 - All Information Is Extracted In The Required Form.

The average scores of the three experts and the final score are presented in the table below.

Summary section	**Average score**
Name and surname	4,8
Post	4,8
Gender	5
Age	5
City of residence	5
Technology stack	3,8
Full experience	5
Working periods	4,8
Functions	4,2
Education	4,6
About yourself (courses)	4,4
Final assessment	**4,7**

Table 1. Results of the evaluation of the formatting of resume files according to a given template

As it can be seen, the model does the worst job of filling the technology stack. The reason is that it does not interpret some technology names as development tools. This problem is solved by adding examples of technologies that the model skips to the prompts. Thus, during re-processing, these technologies will be extracted to the stack.

7.3. Scaling the solution

The integration of a node editor for configuring processing pipelines and downloading a template file allows SmartSearch administrators to configure a digital assistant to automatically process various types of documents according to specified requirements and template. Optionally, the implementation of document processing via Telegram app is available. The created solution is easily scaled to various resume formats. Since we used a modular approach, it only takes a few days to integrate the new functionality. This allows companies to quickly adapt to changing requirements and expand the capabilities of the HR assistant.

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7. Conclusion

In this paper, we have developed AI-pipeline for CV-formatting. The proposed solution significantly automates the process of CV processing of job candidtates, saving up to 6 times of CV-processing time for HR-specialists. We have developed AI-pipeline using DUC SmartSearch platform, a fork of open-source Danswer system. We described AI-pipeline generation and defferent steps, data extraction and LLM communication steps, gave an overview of conceptual architecture, use cases diagram, described main difficulties of LLM-pipeline creation and developed a CV-template.

Additionally, we have tested developed AI-pipeline using different LLMs: Mistral NeMo 12B Q8, Llama 3.1 8B FP16, Saiga-llama3 8B FP16. Fort he best model, a testing methodology was proposed based on processing of 10 random resumes with subsequent evaluation by three independent experts.

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