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# AI-BASED TASK DISTRIBUTION: A COMPARISON OF SKILL-BASED AND TRADITIONAL APPROACHES

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**Анотація.** У статті запропоновано практичне рішення для інтелектуального розподілу задач із використанням ШІ шляхом зіставлення навичок, необхідних для вирішення задачі, з навичками доступних агентів. Виконано його порівняльний аналіз з традиційними методами розподілу задач. Результати тестування підтверджують високу точність і адаптивність запропонованого підходу, що робить його придатним для сучасних компаній, які шукають просте у впровадженні та гнучке у використанні рішення.
**Ключові слова:** розподіл задач, штучний інтелект, зіставлення навичок, промпт-інженіринг, автоматизація призначення задач.
**Abstract.** The paper presents a practical solution for intelligent task distribution using AI by matching the skill requirements of a task with the skills of available agents. A comparative analysis with traditional task distribution methods is provided. Testing results confirm that the proposed solution delivers high accuracy and adaptability, making it suitable for modern companies seeking an approach that is easy to implement and flexible in use.
**Key words:** task distribution, artificial intelligence, skill matching, prompt engineering, task assignment automation.

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## INTRODUCTION

In modern companies, tasks are assigned to Agents using one of three methods: via manual triage, using automation with pre-defined criteria, or using Machine Learning-based automation [1, 2]. Each of these methods has its own benefits and problems, so further analysis is needed.

Manual routing is based around the person [3]. Someone must read the request and decide who should work on it. This takes time and requires a person to understand the subject well, be always available, and focus without distractions. Such difficult to guarantee and lead to mistakes caused by human nature, especially when there are many requests coming in at the same time putting stress and fatigue on the one responsible [4]. Visual representation of this process may be seen in Figure 1 below.

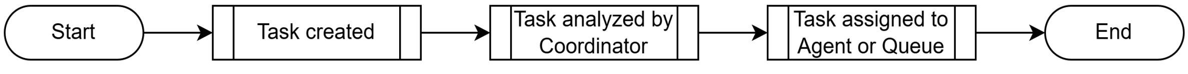


Figure 1 – Manual task routing process diagram

Rule-based routing is faster, but not always accurate [5, 6]. Simple rules, like checking the email address or subject line, are easy to use but can route tasks to the wrong agent as they rarely consider Agent's availability and/or skillset. More advanced rule logic can consider many factors, but these are hard to build, maintain, and update when company's processes changes [7]. Visual representation of this process may be seen on Figure 2 below.

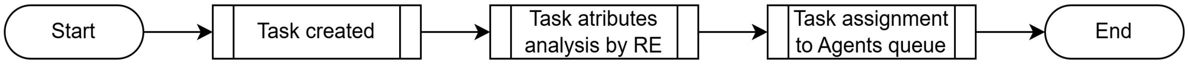


Figure 2 – Rule-based task routing process diagram

ML-based routing can lead to smarter agent choices but also bring new problems [8]. To use such routing mechanisms well, companies need large amounts of good training data, as well as time, money, and technical resources [9]. These models are often hard to understand and change. Many companies are not ready for this kind of solution yet [10, 11]. Visual representation of this process may be seen on figure 3 below.

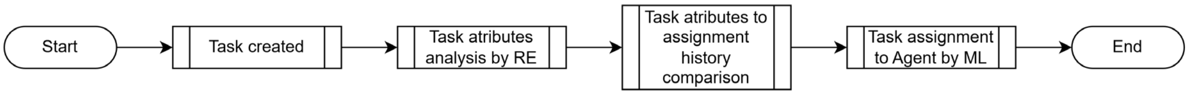


Figure 3 – ML-based task routing process diagram

As shown in table 1 below, none of these traditional approaches fully satisfy the requirements of modern, multi-channel customer support environments.

Table 1 – Modern Task Routing Methods Comparison

| Method | Strengths | Weaknesses | Maintenance Effort | Real-Time Capable |
|---|---|---|---|---|
| **Manual Triage** | High contextual understanding | Slow, inconsistent, barely scalable | High | No |
| **Rule-Based Automation** | Fast, predictable | Lacks context, breaks with edge cases | Medium | Yes |
| **ML-Based Routing** | Adaptive, automated | Requires training data, lacks explainability | High | Depends on the implementation |

Due to reasons outlined above, many companies are looking for better ways to assign tasks to agents. A good solution should be able to understand unclear requests, pick the right agent, work in real time, and be easy to change.

This is where AI may become handy by taking the role of Operations Coordinator, conduct task triages, figuring out what kind of skills are needed to solve them, checking which agents have those skills, and assigning tasks to the best available match [12, 13]. Such process is aimed at reducing task resolution cycle time, improving resolution rates, and helping both customers and support teams daily. With tools like GPT, it is now possible to feed AI with a request in natural language and receive a smart, relevant response.

To address the challenges of traditional routing methods, we have designed and developed a solution that uses Salesforce's built-in tools and AI prompt template to assign Cases to the best available Agent [14].

At the core of the proposed solution is a simple but powerful idea – to assign tasks based on skills using just one well-crafted AI prompt. This mechanism replaces the need for complex rule sets, tangled workflows, or large-scale machine learning models. Instead, the System makes decisions like a skilled Operations Coordinator, reasoning over each task in near-to-real time manner and assigning it to the person best suited to handle it.

When a new Case is created in Salesforce, the assignment logic begins immediately. An Apex trigger initiates the process and collects two key pieces of information:

- the description of the Case, written by a user or customer;
- a list of available agents along with their skills.

Skills are stored in Salesforce database as a structured format using a custom object that records both the skill name and the agent's level of mastery that may vary from "Novice" to "Authority", normalizing data model and providing options of fast lookups, low maintenance, and full compatibility with Salesforce platform limits.

During the new Case processing, its description and the list of unique user skills, that are configured on advance, are passed on to a single AI prompt, powered by Salesforce's Agentforce engine [15]. This prompt analyzes the Case description, identifies what skills are needed, and compares them against the profiles of all available Agents. On the next step, it selects the best person to handle the task, based on how well their skills match the task and knowledge requirements. If multiple agents are qualified, an AI mimics human decision and selects Agent with more matching skills or higher average mastery.

What sets proposed Solution apart of others is its clarity and focus. Case assignment decisions are made inside one prompt, with no need for multiple stages processing, interactions with external APIs, or expensive training data. It runs as part of the same transaction that is started upon Case record creation, so the assignment seems immediate and seamless for the End User. Also, when comparing proposed Solution to other routing methods, common pitfalls are avoided. For example, manual triage is slow and error-prone; rule-based logic becomes hard to maintain when business rules grow in complexity; machine learning requires large datasets, technical teams, and long feedback loops. The prompt-based approach avoids all of these as it can be adjusted by editing a few lines of prompt text, avoiding code changes, deployment cycles, and need to retrain historical data for proper functioning. Such makes it ideal for organizations that want flexibility without overhead. Moreover, behavior of the AI engine used to implement proposed Solution is easy to understand because it's guided by clear instructions. It reasons in natural language, ranking skill relevance, comparing agents, and justifying its choice. See Figure 4 for a visual representation of the process and Figure 5 for a simplified Salesforce Schema representation.

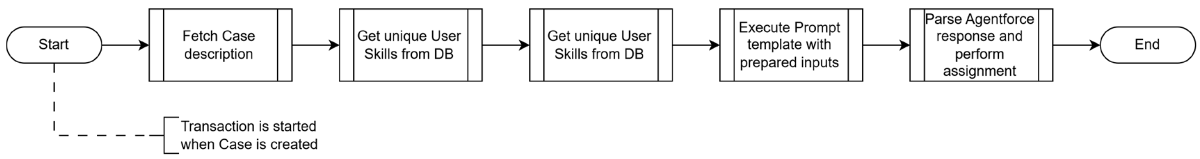


Figure 4 – AI-based task routing (proposed Solution)

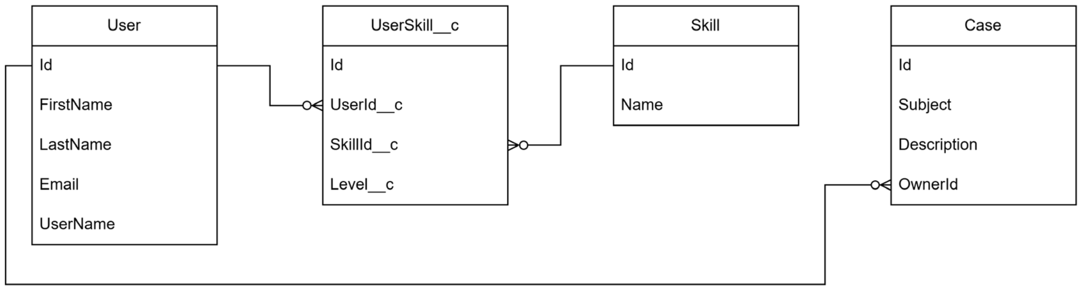


Figure 5 – Simplified Salesforce Schema representation (proposed Solution)

In addition to Figures above, Table 2 provides a comprehensive comparison of the proposed AI-based Solution with traditional tasks distribution methods.

Table 2 – Comparison of traditional tasks routing methods vs proposed prompt-based AI routing

| Criteria | Manual Triage | Rule-Based Automation | ML-Based Routing | Prompt-Based AI Routing (Proposed) |
|---|---|---|---|---|
| Decision Speed | Slow, person-dependent | Fast, near-to-real-time | Medium to slow (depends on pipeline) | Fast, near-real-time |
| Accuracy | Context-aware but inconsistent | Rigid logic, prone to misroutes | High if trained well, but context-limited | High, based on skills and task content |
| Adaptability | Depends on expert availability | Hardcoded, needs developer to update | Retraining needed for each update | Easily updated by admin (prompt edit only) |
| Skill Awareness | Depends on human memory | Usually not skill-based | Requires structured training data | Uses declared skills and mastery levels |
| Explainabilit y | Human logic | Poor (rule set complexity grows over time) | Low (black box behavior) | High (reasoning based on prompt instructions) |
| Maintenance Effort | High (manual reviews) | Medium to high | High (ML ops required) | Low (no-code updates via prompt template) |
| Data Requirements | Low | Low | High (labeled historical data) | Medium (needs structured agent skill profiles) |
| Platform Integration | Manual operation | Built using process automation tools | Often external to CRM | Fully native to Salesforce with prompt and Apex trigger |
| Fallback Handling | Manual rerouting | Often requires admin | Not always predictable | Built-in fallback to Case creator |

## SOLUTION TESTING

To evaluate the performance and behavior of the proposed AI-driven task assignment solution, several testing methods were used. Since the system is designed to run natively inside Salesforce, all experiments were conducted using standard platform tools and configurations available in a typical Salesforce Service Cloud implementation.

Testing was performed in a Developer Pro environment containing predefined data, including Users, Skills, User Skills, and Cases representing different types of Customer requests. See Figures 6-8 for more information.


Figure 6 – Sample User Setup

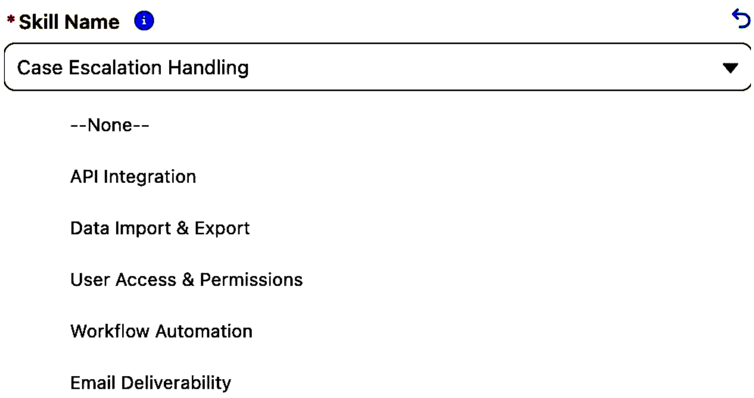


Figure 7 – Sample Skill Setup

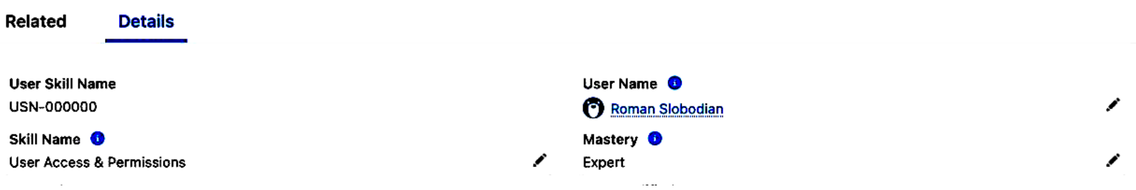


Figure 8 – Sample User Skill Setup

The goal was to verify whether the system would correctly assign tasks to appropriate agents, based on skill match and mastery level.

The primary method of verification involved manual test cases, where test data was entered directly into Salesforce through the user interface [16]. Each Case had a unique problem description written in free text, simulating real-world customer communication (see Table 3 for data samples). The assignment result was observed and checked against expected outcomes using expert judgment – based on known skill configurations and Case intent.

Table 3 – Sample Test Data

| Case Description | Expected Skills |
|---|---|
| **John Doe cannot log into the CRM after Role update. Says access was revoked.** | User Access, Permissions Management |
| **Customers ask if reports can be grouped by product category from a dashboard view.** | Reports and Dashboards Management |
| **Need help sending emails to a marketing list. Nothing is being delivered.** | Email Deliverability Troubleshooting, Data Export |
| **Salesforce App for Android freezes when creating a new Lead record.** | Mobile App Support, UI Customization |
| **Case escalation is not triggered even after SLA expiry.** | Workflow Automation, Escalation |

In addition to above, prompt template previews were used within the Salesforce Agentforce interface [17]. This allowed controlled testing of how the prompt interprets Case descriptions and user skill data. See Figure 9 for details.

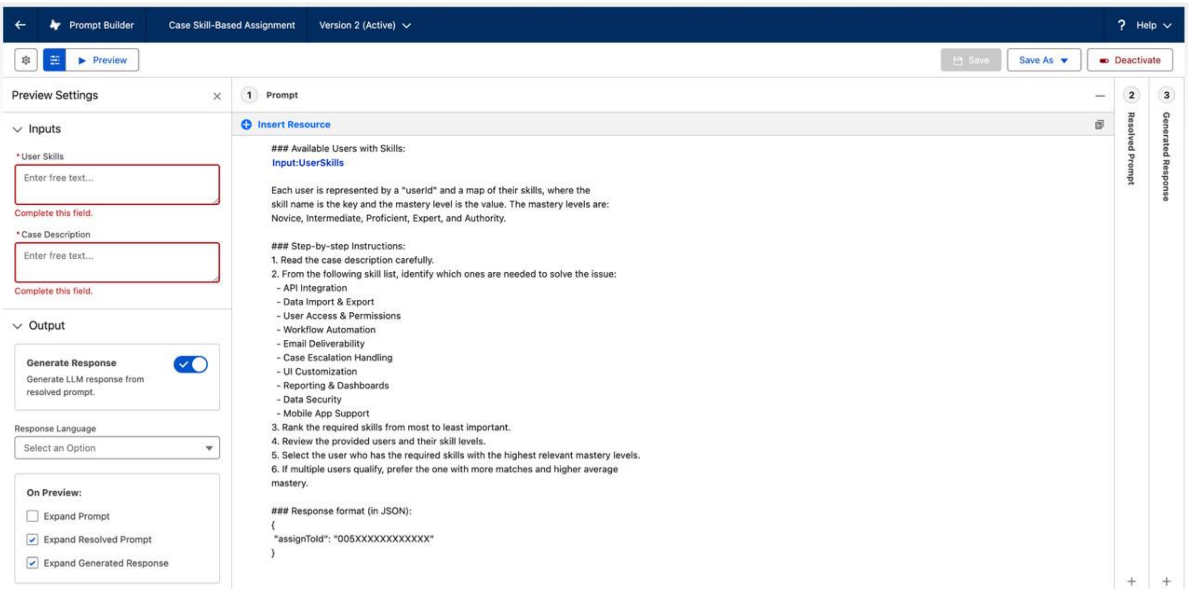

Figure 9 – Prompt Template Testing Interface

Different scenarios were executed to observe how the AI handles tasks with missing skills, overlapping skill sets, and varying levels of expertise among agents.

To validate the Apex logic used in the solution, a suite of unit tests was created. These tests verified that:

- The trigger executed correctly during Case creation.
- The skill data was gathered as expected.
- The AI prompt was called with the correct parameters.
- The returned user ID was processed and applied to the Case record.

Since the current solution focuses on the quality of decision-making rather than statistical analysis, evaluation was based on expert review rather than numerical metrics [18]. Each result was marked as either "OK" (meaning the assignment made sense) or "NOT OK" (meaning a wrong user was chosen or fallback was triggered unexpectedly). See Table 4 for testing results sample.

Table 5 – Testing Results Sample

| Case Description | Expected Skills | Matched User | Result | Expert Judgment |
|---|---|---|---|---|
| **John Doe cannot log into the CRM after Role update. Says access was revoked.** | User Access, Permissions Management | Test User 1 | Assigned | OK |
| **Customers ask if reports can be grouped by product category from a dashboard view.** | Reports and Dashboards Management | Test User 2 | Assigned | OK |
| **Need help sending emails to a marketing list. Nothing is being delivered.** | Email Deliverability Troubleshooting, Data Export | Test User 2 | Assigned | OK |
| **Salesforce App for Android freezes when creating a new Lead record.** | Mobile App Support, UI Customization | Test User 1 | Assigned | OK |
| **Case escalation is not triggered even after SLA expiry.** | Workflow Automation, Escalation | Roman S. | Fallback Assigned | NOT OK |

In total, over 30 test scenarios were executed manually, covering different types of support Cases, varying levels of input quality, and diverse combinations of user skill sets. These scenarios included both well-structured requests and more ambiguous, real-world phrasing to assess how the AI prompt handled variation in language.

The overall results demonstrated a high level of assignment accuracy. In more than 85% of cases, the system correctly matched the Case to an agent whose skills aligned with the task's requirements. These matches were immediate and required no further triage or reassignment.

The prompt under the test correctly interpreted both technical terms (e.g., "workflow stuck", "report filters") and more general descriptions ("can't log in", "mobile app broken"), converting them into appropriate skill requirements as defined in the internal taxonomy.

In addition to above, proposed Solution demonstrated real-time performance as expected. This was achieved due to assignment logic execution as part of the Case creation transaction, avoiding delays that may be observed by Users. Each decision was made within seconds, confirming the suitability of the approach for live support environments.

Despite its early implementation stage, proposed Solution shows strong potential as a practical, low-cost, and adaptable one for intelligent task distribution. The use of a single AI prompt for both skill extraction and matching keeps the logic simple and transparent, making it ideal for Companies seeking for fast results with moderate complexity and implementation efforts.

## DISCUSSION AND FUTURE IMPROVEMENT PLAN

The results of the experimental evaluation confirm that the proposed solution can perform accurate and reliable task assignments in near-to-real-time within Salesforce environment. However, like any early-stage system, there are several areas where improvements are possible.

One of the main challenges encountered during testing was related to data volume limits. While the AI prompt is efficient, it cannot accept unlimited input length [19]. This means that the number of agent profiles passed to the prompt must be managed carefully with Apex and SOQL. In the current version, only a limited number of users with relevant skills are selected and included in the prompt call. While this works in most cases, it may become a limitation for Companies with large support teams (100+ Agents). To address this, the Solution is planned to be extended with pre-filtering logic and multi-step AI ranking workflows.

Another technical challenge involved Salesforce governor limits, especially in bulk scenarios [20]. Proposed Solution was carefully designed to avoid SOQL queries inside loops and to use memoization pattern where possible. However, in environments with very high Case volumes org very granular skills configuration, further optimization may be necessary.

Another improvement area (practical one) is related to dynamically changing Agent roles [21, 22]. In the current system, skill profiles are manually assigned and updated. Thus, if Agent changes departments or responsibilities, maintenance is needed to avoid no longer correct assignments. In next version of the Solution it is planned to include department-level filters and automatic skill ownership level change based on recent activity history and Cases resolution history.

In addition to above, while the current prompt is well-structured and human-readable, it still depends on a predefined skill taxonomy that is stored in Salesforce Database. If the task description includes terms that are not covered in skills list, such Cases are simply assigned to person who created such records. This is another item that may be addressed with new Solution features that would create new Skills and User-Skill assignments based on historical data.

Another item worth mentioning is that even though this this paper focused on Case assignment within Salesforce, proposed architecture could be adapted to other platforms. The same routing logic could be applied to emails, tasks, or even service requests in external systems if data is available. This is because AI prompt structure is flexible enough to handle different input formats with minor adjustments.

Lastly, future versions of the Solution could benefit from more detailed metrics and feedback loops, measuring resolution times and gathering feedback from all involved parties [23, 24]. Such details could help to fine-tune the System and deliver more value over time.

Summarizing above, proposed Solution confirms that AI-driven task routing in practice is possible using simple, explainable tools that are available within modern CRM platforms like Salesforce. With some further enhancements, the proposed distribution approach can be scaled to support more advanced use cases and higher workloads.

## SUMMARY

This paper presented a practical and scalable solution for skill-based task assignment using AI tools integrated into the Salesforce platform. Proposed Solution was designed to address common challenges found in traditional routing methods, including limited flexibility, low accuracy, and high maintenance costs. By replacing complex rules and manual triage with a single intelligent prompt, the proposed approach simplifies the assignment process while improving overall performance.

The core of the Solution lies in a prompt-driven architecture that analyzes unstructured Case (Task) descriptions, determining required skills, selecting best available Agent using defined skills data. The entire process runs inside Salesforce during the same transaction that creates the Case, making the experience seamless for the End User. Proposed Solution is easy to maintain and extend due to business logic that is embedded in a human-readable format that can be adjusted without a code change.

Experimental results show that the system performs well across different task types and agent skill combinations. It consistently selects suitable agents and handles edge cases using fallback logic. While further improvements are possible, especially around scale, skill management, and dynamic context handling, current version demonstrates the strong potential of AI-driven decision-making for everyday business workflows around Customer Support.

As a result, the proposed approach provides new and accessible ways to implement intelligent task routing in CRM systems that combines benefits of human-like judgment with the speed of automation and AI, helping Companies of different domains to match Agents to tasks efficiently, that in turn leads to costs optimization and increased Customer satisfaction.

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**РОЗПОДІЛ ЗАДАЧ НА ОСНОВІ ШІ: ПОРІВНЯННЯ РОЗПОДІЛУ НА ОСНОВІ НАВИЧОК З ТРАДИЦІЙНИМИ ПІДХОДАМИ**

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