SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2025
ORGANIZATION AND MANAGEMENT SERIES NO. 235

DO AI AGENTS ENHANCE PROCESS OWNER WORK AND DECISION-MAKING? AN EXPERIMENTAL VERIFICATION ATTEMPT

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Purpose: The paper examines how AI-driven multi-agent systems can transform business process management by augmenting the activities of process owners.
Design/methodology/approach: The research employs controlled simulations in which diverse AI agents collaborate in configurations like self-discovery, map-reduce and debate to generate, evaluate and select optimal process variants.
Findings: Experiments show that multi-agent systems have the potential to enhance process owners' ability to manage changing workflows by enabling parallel evaluation of alternative designs. Agent configurations uncover novel courses of action and balance the exploitation of proven methods with the exploration of new possibilities, leading to better decision outcomes.
Research limitations/implications: The study's reliance on simulated environments limits generalizability, requiring real-world validation across varied industries.
Practical implications: Organizations adopting MAS must invest in workforce reskilling and role redesign to foster effective human–agent teamwork and an innovation-driven culture. Deployment of these systems can accelerate process optimization cycles, reduce time-to-market for changes and enhance customer responsiveness.
Social implications: The large-scale adoption of AI-driven multi-agent systems will redefine many roles, making continuous reskilling a prerequisite for employability while nudging organizations to cultivate a culture of innovation and learning.
Originality/value: This paper uniquely tests multiple agent configurations—self-discovery, map-reduce and debate—within BPM to reveal their complementary strengths in process innovation. It provides a novel framework for balancing exploration and exploitation in organizational design and is valuable to both researchers and practitioners seeking agile, AI-powered process management.
Keywords: AI agents, Multi-agent systems, AI agents in BPM.
Category of the paper: Technical paper, Research paper.

Description of the analyzed (FADO) company, agent workflows and raw outputs are available at the URL: **https://ceopedia.org/pub/index.html**

1. Introduction

The concept of an agent has been widely explored across disciplines, including organizational and management theory (Eisenhardt, 1989; Lan Heracleous, 2010). AI agents are artificial entities designed to perceive their environment, make decisions, and execute actions (Wooldridge, Jennings, 2010). Language models (LMs) can be used as a mechanism that allows AI agents to operate effectively in a variety of settings (Park et al., 2023). LMs enable such agents to reason, plan and act within the environment in which they operate (Kaddour et al., 2023). This means that agents, embodied or not, can perform even complex and demanding tasks or processes in the organizational domain. LM-powered agents can achieve user-prompted goals by employing a proper strategy and breaking it into smaller, manageable tasks (Zhiheng, 2023). More advanced solutions anticipate the collaboration of multiple agents to solve complex problems by leveraging the cognitive synergy of multiple autonomous agents (Hong et al., 2024). LM-based agents can also acquire interactive capabilities by learning from feedback and self-evolving (Schick et al., 2023). This results in LM-based agents having the potential to perform even complex tasks or processes that are currently within the domain of humans.

The current level of development of LM-based agents enables their application in business process management, both in automation and augmentation (Raisch, Krakowski, 2020). This means that agents can perform routine and repetitive tasks and also help in decision-making (Park et al., 2023; Zhiheng, 2023). Single-agent solutions use specialised agents to perform specific tasks. These solutions focus on the internal mechanisms of the agent, including the effectiveness of tool usage and their ability to interact with the environment. Such solutions can automate routine tasks or processes (Schwartz et al., 2023). Due to their ability to solve complex problems through a synergy of multiple agents, multi-agent solutions can be useful in augmenting the potential of process actors. Thanks to the cooperation of many appropriately profiled agents using language models as a reasoning engine, it is possible to solve complex problems, considering many different conditions and perspectives (Liu et al., 2024; Guo et al., 2024). Organisations should focus on augmentation rather than on automation because augmentation demands continued human involvement, creativity, and experimentation, which creates more lasting sources of competitive advantage (Daugherty, 2018). The question arises whether LM-based agents can augment process owners' abilities to manage dynamic business processes. Can multi-agent solutions increase the capabilities of process owners, enabling them to explore new possibilities and effectively exploit existing certainties? The question is relevant, as the existing literature clearly underscores the importance of examining the impact of digital technologies and digital transformation on the evolving role, emerging challenges, and requisite competencies of process owners (Danilova, 2018).

This article aims to verify whether and to what extent AI agents can augment process owner capabilities in effectively managing variable and dynamic processes. The planned research assumed designing and implementing selected multi-agent solutions and testing their potential as solutions supporting the process owner. Conducting such empirical verification allowed for indicating the application areas of these solutions and identifying the potential benefits for process actors from their use. The research results can constitute the basis for formulating practical recommendations for implementing multi-agent systems and their optimisation in managing dynamic business processes.

2. AI Agents Theory

The development of language models has significantly increased the potential usefulness of AI in the area of organisational management. Although those models generate mostly correct results, their probabilistic nature means that they may provide false information or hallucinate (Händler, 2023). It should be noted, however, that these shortcomings are increasingly eliminated in subsequent generations. Additionally, these models lack knowledge of the specifics of a specific organisation, the environment in which it operates and the realities of the problem that language models help solve. This meant that the use of these models in the area of organisation management was not adequate to the potential of this solution. These limitations resulted in the need to design more flexible solutions, including those that take into account agents. LM-based agents are able to achieve user-defined goals by using a strategy that involves breaking them down into tasks to be performed (Zhiheng, 2023). More advanced solutions provide for the cooperation of many agents to deal with complex problems using the cognitive synergy of many autonomous agents. Multi-agent solutions (MAS) are based on the cooperation of many agents to deal with complex goals (Park et al., 2023). In such solutions, agents assume distinct roles encompassing agent characteristics, behaviours and capabilities (Guo et al., 2024). Multiple LM-powered agents jointly perform tasks, each equipped with unique strategies and engaged in communication with one another (Park et al., 2023). These agents may cooperate or compete with each other, while information exchange between them can occur in a centralised or decentralised manner. An important advantage of multi-agent solutions is that agents can obtain feedback not only from the user or the environment, but also from other agents (Wang et al., 2023). This enables agents to adjust their profiles or goals, rather than just learning from historical interactions (Guo et al., 2024). It also allows agents to acquire new capabilities and utilise new tools (Schick et al., 2023). The following multi-agent frameworks are currently the most popular: LangGraph (LangGraph, 2025), CAMEL (Li et al., 2023) and AutoGen (Wu et al., 2023).

A review of the relevant literature confirms that the process owner is responsible for the entire lifecycle of a process, making this role one of the most multidimensional within BPM (Danilova, 2018). The role encompasses both operational responsibilities – such as process design, standardisation, documentation, and performance measurement – and exploratory tasks, which involve seeking new solutions, differentiation, risk-taking, experimentation, and discovery (Rialti et al., 2018). To carry out these activities effectively, process owners must continuously monitor the competitive environment, technological advancements, and evolving customer needs (Trkman et al., 2015). This enables them to identify, assess, and prioritise improvement needs, as well as to pinpoint areas with the greatest potential for innovation. At the same time, the growing complexity of processes, market dynamics, and the exponential increase in data and information render traditional methods of process management increasingly inadequate. In this context, emerging technologies – particularly artificial intelligence – have the potential to fundamentally transform both the scope and execution of the process owner's responsibilities (Danilova, 2018).

LMs primarily support process owners in processing and interpreting available data and information. In contrast, MAS are better equipped to handle more complex tasks, conducting advanced simulations and analysing diverse scenarios and decision-making situations (Park et al., 2023; Guo, 2024). They are particularly useful for tasks carried out in multiple stages and requiring the exchange of outputs generated at various steps within a workflow. For the process owner, this translates into support in three key areas (Danilova, 2018). Firstly, automating routine analyses frees up time for generating new ideas and exploring additional opportunities. Secondly, the ability to conduct simulations and in-depth analyses of potential scenarios reduces the risks associated with experimentation by providing fast and reliable feedback prior to the design and implementation of changes. Thirdly, the multi-agent architecture naturally reflects the cross-functional nature of processes. Each agent can represent the interests of a different function or stage, enabling a multi-perspective analysis and reducing the risk of sub-optimisation. As a result, AI does not replace the process owner, but rather broadens their perspective and enhances their responsiveness to environmental signals. This facilitates the reconciliation of exploitation and exploration needs and reinforces the process owner's strategic position within the organisation.

3. Method

A series of quasi-experiments were conducted to verify the assumption that MAS can augment process owners' work. They aimed to assess the suitability of selected multi-agent architectures for tasks that reflect real problems and situations encountered in an enterprise (Ross, Morrison, 2004). The experiments were based on the example of a hypothetical company, FADO, which was specifically developed for the purposes of this study. This approach enabled the researchers to examine how agents contextualise business realities while performing tasks, while also limiting environmental complexity and allowing selected MAS configurations to be tested under strictly controlled conditions. In the first series of experiments, all agent configurations were assigned the same task. This allowed for the validation of the correct functioning of each MAS configuration. In the second series, however, the agents within each configuration were given different tasks, simulating those typically performed by process owners within an organisation (Danilova, 2018). The two-stage research design was developed to test the hypothesis that MAS can effectively support process owners in the areas of process improvement and innovation. The experiments were conducted in December 2024 and January 2025.

3.1. Used case study

FADO is a hypothetical company created solely for the purposes of these experiments. It manufactures home appliances and is the leading budget-segment brand of washing machines and refrigerators in Poland and Eastern Europe. The company operates modern production facilities and employs a highly skilled workforce. Its competitive advantage lies in the reliability of its products, while challenges remain in the form of high manufacturing costs and less appealing design. The company's key processes include market research and marketing, the design of modern products, production planning and execution, procurement, and logistics, culminating in fast after-sales service. FADO is in the process of implementing an ERP system and con-ducting intensive training programs aimed at reducing costs, shortening delivery times, and successfully entering Western European markets. A complete description of this hypothetical company is available in the repository (*0_FADO_company_description_EN.pdf*).

3.2. Quasi-experiments idea

As part of the study, three distinct configurations of MAS were designed and implemented to support the process owner. Each configuration was initially tested on the same benchmark task ("How to improve operational agility in FADO"), which enabled the validation of their correct functioning. This included assessing the reasoning techniques employed, the structure of the workflows, and the overall quality of the outcomes generated by each configuration.

In the second series of experiments, the MAS configurations were applied to three clearly defined areas of the process owner's responsibility:

- Environmental and competitive analysis – identifying and organising in-formation about FADO's market and product competitors (and, by ex-tension, their processes), followed by the formulation of recommendations concerning FADO's own product portfolio and operations (Trkman et al., 2015).

- Scenario and process change analysis – generating and evaluating pro-posed process modifications based on two approaches: exploration of new possibilities and exploitation of established certainties, in order to select the most advantageous variant (Danilova, 2018; Khan, Mir, 2019).
- Multifaceted process change discussion – integrating the perspectives of various process stakeholders within FADO to minimise the risk of over-looking critical constraints and to avoid sub-optimisation when designing or redesigning processes (Ohlsson, Han, 2018).

This approach allowed for the assessment of how agents contextualise business realities while performing tasks, and confirmed that MAS configurations can effectively support process owners. The conclusions were based on the evaluation of selected MAS architectures in tasks reflecting real-world problems and scenarios encountered in enterprise environments. The use of a simplified description of the hypothetical company, along with carefully selected MAS configurations, helped to reduce complexity and maintain experimental clarity (Ross, Morrison, 2004).

3.3. Description of implemented configurations

MAS configurations were implemented using the LangGraph library (LangGraph, 2025). The concept of state agents was used, in which agents cooperate and save information that is key to the workflow in the state. This is a form of repository that is available to all agents involved in the work (Wu et al., 20024). The workflow between agents is defined in the form of a graph. These properties make this solution extremely useful in implementing customised multi-agent configurations. In the case of those configurations, they exchange the results of their work through the use of the state. The language model used by the agents was a model ”gpt-4o” and a reasoning model “o1-preview”. The aspects of the chosen configurations that can support the process owner were also investigated. The experiments included three variants based on the following approaches: self-discovery, map-reduce, and debate.

The self-discovery approach allows agents to discover key areas for a given task independently and to conduct reasoning subordinate to the execution of such a task. The logic of this approach assumes the use of task decomposition as well as sequential processing. It assumes that first, appropriate areas of reasoning are selected from among the available ones (self), and then, based on them, a reasoning process is developed (discovery), which leads to solving the task or explaining the problem (Zhou et al., 2024). The tested configuration included three agents using a Chain of Thoughts as a generally defined way of reasoning (Wei et al., 2023). The select agent indicated key areas of analysis selected from many available ones. The structure agent developed subsequent stages of the plan that should be implemented to solve the problem stated by the user. On the other hand, the reason agent (based on the reasoning model) prepared specific solutions or tasks necessary to be implemented within each stage. The workflow structure within the self-discovery variant is presented in Fig. 1a.

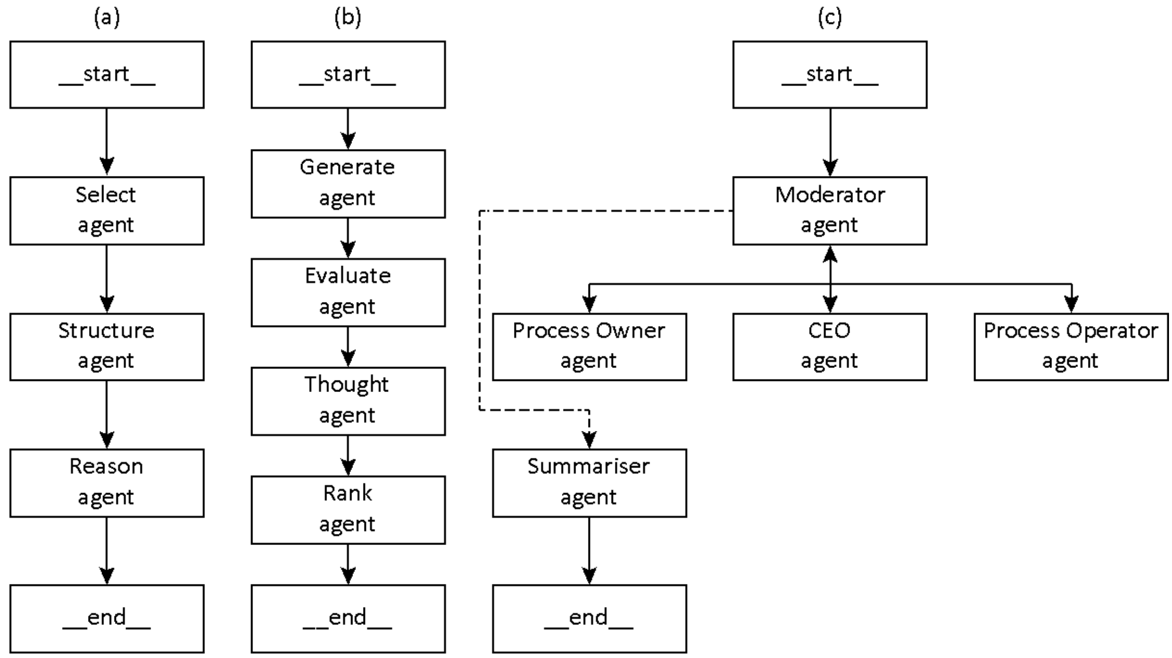

Figure 1. Workflow for self-discovery (a), map-reduce (b) and debate (c) agents.

Source: own study.

The map-reduce approach allows agents to analyse many possible variants of a problem solution, evaluate them, and choose the best one. The logic of the approach uses task decomposition and parallel processing (LangChain, 2025). It assumes that the task is first divided into smaller subtasks, then each subtask is executed in parallel (map). Finally, the results from all completed parallel subtasks are aggregated, and the best way to complete the task is selected (reduce). In this case, the agent configuration used the Tree of Thoughts as the initial way of reasoning (Yao et al., 2023). The test configuration included four agents. The generate agent employed a reasoning model to produce solutions. The evaluate agent conducted an overall assessment and issued a recommendation. The thought agent performed an in-depth analysis of each solution and its evaluation, considering various aspects of the problem defined by the user (i.e. potential scenarios or possible implementation strategies). The rank agent selected the best possible variant from those deemed. The workflow structure within the map-reduce variant is shown in Fig. 1b.

The debate approach assumes profiling agents and joint discussion to achieve an optimal solution to the problem. The logic of this approach is based on sharing in-formation and exchanging opinions between agents, which allows for in-depth analysis and obtaining a multi-faceted view of the problem (Liu et al., 2024). All messages agents exchange in saved in a common repository, allowing access to conversations' history (Shared Messages Pool with History). The test configuration included five agents. Process owner agent, whose task was to represent the interests of the process owner. Process operator agent, who focuses on the operational aspects of the process. CEO agent, who analysed the problem from a management perspective, considering the company's development and its strategy's implementation. Moderator agent, whose role was to coordinate the discussion, determine the order of statements and provide guidelines for other agents. At the end of the process, the summariser agent summarised the results of the conversation and indicated the main conclusions and recommendations. Each agent participating in the discussion had the opportunity to refer to standard information, propose new solutions or question the presented arguments, which allowed for modifying the presented point of view. The workflow structure within the agent's debate variant is given in Fig. 1c.

4. Results

4.1. Validation of MAS configurations

In the initial phase of the study, a series of quasi-experiments was conducted to verify the functionality and effectiveness of three selected MAS configurations. All tests were based on a common benchmark task: How to improve operational agility in FADO? This uniform benchmark enabled a comparative analysis of the configurations' performance and allowed for an assessment of the integrity and coherence of their reasoning mechanisms. The primary objectives of the experiments were as follows:

- Verification of implementation correctness – assessment of whether agents within each configuration interact appropriately and whether the shared state is correctly accessed and updated in accordance with the predefined workflow.
- Evaluation of the reasoning techniques employed, specifically: Chain of Thought (self-discovery), Tree of Thought (map-reduce), and multi-stage argument exchange (debate).
- Assessment of output structuring mechanisms – determining whether the generated outputs conform to the desired format and are properly parsed.
- The results confirmed that all three configurations functioned correctly and processed the task per the intended design. A complete summary of the results from this test series is available in the file provided in the repository: (*1_d_TEST_Summary_of_Agents_experiments_results_ENG.pdf*).

4.2. Results of the quasi-experiments

In the second stage of the experiments, the focus shifted to evaluating how the implemented configurations would perform when tasked with activities typically carried out by process owners. Accordingly, each configuration was assigned a distinct task corresponding to a specific function fulfilled by a process owner (Table 1).

Table 1.
Tasks for the configurations corresponding to specific project owner activities

Process owner activity	MAS configuration	Task for AI agents
Environmental and competitive analysis (21)	Self-discovery	Isolate FADO competitors and prepare a strategy for dealing with them in the context of changes in FADO business processes
Scenario & process change analysis (14, 23)	Map-reduce	The FADO manufacturing process is not very flexible; suggest changes that can be introduced to this process (one operational, the other exploratory) to improve its results.
Multifaceted process-change discussion (24)	Debate	At the meeting, you are to discuss the idea of the Modular configurator "FADO Build". Description of the idea: The online customer independently “assembles” their household appliances, choosing from the module libraries (chamber, engine, panel, front, accessories). After finalisation, the system generates a personalised specification and passes it directly to production.

Source: own study.

The experiment results indicate that the tested configuration enables agents to act in a structured manner adapted to the specifics of the problem they are trying to solve.

Table 2.
Results of the self-discovery configuration experiment (examples)

Competitors’ behaviour	Impact on the FADO process	Recommended changes in FADO operations
Premium brands (Bosch, Siemens, Miele) are intensively developing smart and eco-technologies – intelligent control, integration with mobile applications, energy-saving solutions.	Product development	“Focus on products with growth potential, such as induction hobs, investing in their promotion and development”.
The premium segment emphasises modern design and prestige as a key value.	Product development	“Invest in the design department, employing creative designers or cooperating with external design companies to create modern and attractive designs”. “Conduct research on aesthetic preferences in target markets to adapt products to customer expectations”.
Budget competitors (Beko, Amica) systematically minimise production costs, maintaining acceptable quality.	Production	“Analyse production processes in terms of efficiency and look for opportunities to reduce costs without losing quality (e.g. through lean manufacturing)”. “Implement automation and new technologies in production”.
Premium brands build trust through long warranties and consistent communication reliability.	Service	“Introduce longer warranties or service programs to build customer trust”. “Highlight the high quality and reliability of FADO products in marketing campaigns”.
Mid-market competitors retain customers through loyalty programs and after-sales service.	Service	“Implement loyalty programs and after-sales service at a high level”. “Collect customer feedback and implement improvements based on it”.

Source: own study.

Analysis of the assumptions of the self-discovery approach, the way agents operate, and the results of their work indicate the potential usefulness of this solution for the process owner. It makes it easier for the owner to identify critical areas of analysis. It supports sequential and structured examination of the essence of the problem that the process owner is dealing with (Table 2). The experimental results specifically illustrate how competitors' actions impact individual processes carried out within FADO. As a result of its operation, the self-discovery configuration transforms dispersed market signals into a coherent set of recommendations encompassing the entire value chain – from research and development and design, through production and marketing, to after-sales service. Consequently, the process owner receives not only a clear picture of the competitive landscape but also a concrete projection of the changes the enterprise must implement in order to maintain its advantage in a rapidly evolving market environment. This configuration can be further enhanced by equip-ping the agents with tools that enable direct access to competitors' websites and social media channels, thereby allowing them to operate on even more up-to-date data.

The map-reduce approach enabled agents in this configuration to generate two solutions to the problem, perform their in-depth analysis, and select the best possible solution. The experiment results show that the map-reduce approach allows agents to generate various potential solutions to the problem, evaluate them, and perform in-depth analysis based on current business realities. Agents can also indicate the best solution, considering specific elements or aspects of each solution (Table 3).

Table 3.
Results of the map-reduce configuration experiment (examples)

Character of a change	Title and description of a change	Main assumptions
Exploitation	**Smart Production Booster** The implementation of an advanced ERP system will integrate planning, purchasing, warehouse, production, distribution and service and add real-time analytics to track performance. Such data consistency will shorten lead-time, enable rapid response to demand and reduce unit costs.	Full ERP implementation – "Implementation of an advanced ERP system that will integrate all key processes – from production planning, through purchasing, warehousing, to distribution and service". Process integration – "Implementation of an ERP system allows for the integration of all key processes, which can lead to better coordination and operational efficiency". Analytics and rapid response – "Using data analytics and real-time monitoring systems, which will enable rapid response to changing market conditions…". Cost reduction – "…which will consequently reduce unit production costs…". Better adjustment to demand – "…and respond faster to customer demand".

Cont. table 3.

Exploration	**SmartHome Design Lab** An interdisciplinary R&D team will develop modular household appliances configured online and natively integrated with smart-home ecosystems, distinguishing the offer with modern design. Rapid pilot and iteration will enable testing of concepts and introduction of innovations before the competition.	R&D team and new products – “Creation of a dedicated, interdisciplinary R&D team…”. Attracting young customers – “Modern products can attract young consumers…”. Advantage through smart home – “…integration with smart home systems increases the attractiveness of the offer”. Rapid iteration and market testing – “Pilot implementation… to collect feedback and quickly iterate the design”. Flexible adjustment of trends – “…which will allow for quick testing of new concepts and integration with smart home systems, while meeting the tastes of young customers”.

Source: own study.

As a result of the map-reduce configuration’s operation, the process owner receives proposals for changes in the process that are both exploitative and explorative in nature. Each proposed solution is then subjected to detailed analysis regarding its feasibility, potential scenarios, and implementation strategies. This multidimensional analysis enables the process owner to simplify the decision-making process and ensure its transparency, thereby guaranteeing greater objectivity in the initiation and implementation of process changes. As a consequence, the risks associated with such changes are minimised, and optimal change pathway – whether exploration or exploitation – is selected.

The debate approach allowed agents to have a joint discussion to find a solution to the problem (Table 4).

Table 4.
Results of the debate configuration experiment (examples)

Stakeholder	Point of view	Statements from the debate
CEO	**Holistic business-technology strategy** Synchronised integration of 3D configurator with ERP/MES and flexible assembly line is to simultaneously: (1) reduce unit cost, (2) shorten time-to-market, (3) strengthen customer loyalty through mass customisation.	*“The idea of modular configurator ‘FADO Build’ is promising... Integration with ERP/MES systems and flexible assembly line can significantly improve production efficiency”.* *“...integration of customer preference data with ERP can significantly increase FADO's operational efficiency, which is important in the context of product personalisation and building loyalty”.*
Process Owner	**Just-In-Time orchestration based on customer data** Management of module buffers and current feeding of ERP with preference data allows dynamic balancing of demand and line capacity, eliminating bottlenecks with minimal inventory cost.	*“When considering the ‘FADO Build’ concept, it is crucial to integrate Just-In-Time logistics with a modular approach to minimise the risk of delays”.* *“Inventory and supply management are key, but customer preference data can be just as important… If we can integrate them with ERP, we can better predict demand”.*
Process Operator	**Operational stability of production** To avoid chaos after implementing the configurator, you need: (1) clear procedures for issuing modules, (2) advanced, preferably AI-supported, inventory planning, (3) intensive training so that each operator understands the new tools and can react quickly to configuration changes.	*“Okay, but how do you organise all this so that it actually works?... You have to be careful not to end up with chaos in the warehouse and delays in production”.* *“Maybe it’s worth considering using advanced inventory management systems that use artificial intelligence to predict demand”.* *“Without proper training, even the best ERP system is just an expensive gadget… employees need to know how to get the most out of it”.*

Source: own study.

The experiment testing the debate configuration showed that agents representing different roles engage in discussion, indicating and analysing solutions to the problem from various perspectives. This solution allows key process participants to examine the perception of potential process changes. Such a simulated discussion can also be conducted by the owners of individual processes, considering the impact of possible changes on the entire process system. This allows for the analysis of changes in business processes from the point of view of different roles without the need to engage them in such a discussion. It shows the process owner the aspects of the introduced changes that are important for individual process participants and how they perceive potential changes, including what they are afraid of, how they may react, etc. Additionally, using this configuration of agents allows the process owner to plan the implementation of process modifications (e.g., reengineering projects) better, identify potential resistance and optimise communication strategies, which can lead to reducing resistance to change or gaining acceptance for the introduced change. The complete results of the experiments can be found in the repository:

– *2_a_RESERACH_Self_discovery_agents_raw_output_PL.pdf,*
– *2_b_RESERACH_Map_reduce_agents_raw_output_PL.pdf,*
– *2_c_RESERACH_Agents_debate_raw_output_PL.pdf.*

Naturally, the presented configurations can complement one another and operate within a larger system as subgraphs. When such a more complex system receives a command from the user, it autonomously identifies the task type based on its own analysis and activates the appropriate subgraph with the corresponding agent configuration. The system can also be further expanded by incorporating additional con-figurations to support the process owner in new, previously unaddressed domains (14). This approach enables the solution to be scaled according to the specific needs of a given process owner.

The final stage involved three process owners, one from a manufacturing firm, one from a service company, and one from a hybrid enterprise, evaluating the performance of the three configurations. Their assessment results are shown in the table below. Each configuration was rated on a five-point scale, where 1 means "offers very little support" and 5 means "offers very strong support.

Table 5.
Results of the debate configuration experiment (examples)

MAS configuration / PO task	Process Owner (Manufacturing)	Process Owner (Services)	Process Owner (Hybrid)	Average Rating
Self-discovery *Environmental & Competitive Analysis*	4.0 – "May facilitate quick market scanning, competitor monitoring and R&D investment prioritization through automation".	3.5 – "Can highlight competitors' moves, but needs CRM integration to exploit its full potential."	3.5 – "Helpful for scanning the market and competitor actions, but still requires refinement".	3.7

Cont. table 5.

Map-reduce *Scenario & Process-Change Analysis*	4.0 – "Provides several improvement variants, although their analysis is rather simplified. I quickly chose the most interesting one".	4.0 – "Potentially useful for analyzing process improvements, but calls for deeper analyses and comparisons."	4.5 – "Enables assessment of various variants and change scenarios. Potentially very useful in a volatile environment."	4.2
Debate *Multifaceted Process-Change Discussion*	3.5 – "Captures different viewpoints and roles in the process, but needs further development".	4.0 – "An interesting way to analyse how changes are received. Won't replace meetings but is a good tool for preparing discussion threads."	4.0 – "Allows simulation of different attitudes; I'm not sure it can model fears about upcoming changes."	3.8

Source: own study.

5. Conclusions

Adopting AI-driven multi-agent systems presents substantial opportunities for organisations seeking to enhance their business process management. These systems have demonstrated their potential to significantly increase operational agility and improve customer satisfaction by enabling dynamic, flexible solutions that evolve with business needs. By exploring multiple solution paths concurrently, AI agents offer an agile approach to decision-making and problem-solving that traditional methods cannot match.

The experiments have shown that they can strengthen the process owner's ability to manage dynamic and changing business processes (Badakhshan et al., 2019). Configurations such as self-discovery, map-reduce and agent debate allow process owners to discover new ways of acting, experiment and choose the best way of acting in a given situation. Agents using different approaches and functioning in different configurations allow process owners to analyse many possible solutions (as well as their variants) and deliberately choose the best one. Using multi-agent solutions can improve the process owners' ability to balance exploring new possibilities and exploiting existing certain-ties (Rialti et al., 2019). Using different agent configurations can also strengthen the process owners' ability to unlearn established ways of doing things, and to learn new ones, allowing them to create new processes (or their variants) or look for other ways to improve them (Miller et al., 2012; Klammer, Gueldenberg, 2019). Therefore, MAS can positively impact an organisation's adaptability, leading to better implementation of business goals and greater customer satisfaction. The experiments highlight the capability of agents to integrate imitation learning and adapt to evolving business contexts, promoting continuous improvement and reliability. There is a compelling need for ongoing research to refine these mechanisms, ensuring robust and contextually relevant task execution.

Introducing AI agents into business processes will inevitably reshape the work-force, necessitating a proactive approach to reskilling and redefining roles to ensure seamless collaboration between humans and agents (Daugherty, 2018). This transition will also require fostering an organisational culture focused on innovation and continuous learning. Despite the promising results, ethical and security considerations must be addressed to realise the potential of AI-powered multi-agent systems fully. Building robust frameworks that ensure transparency, accountability, and compliance with moral norms is critical to mitigating data privacy and bias risks. Future research should aim to enhance agent architectures to support complex decision-making and improve natural language processing for better human-agent interaction. Exploring adaptive learning mechanisms and strategies will empower agents to thrive in dynamic environments, optimising business processes and driving sustainable growth.

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