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Research on the Collaborative Mechanism and Effectiveness Evaluation of AI Agents in End-to-End Enrollment Operations

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Abstract: Against the backdrop of the sustained advancement of education digitalization, higher education enrollment has placed higher demands on precision and efficiency. Because traditional enrollment models are fragmented across stages and isolated in terms of data, they can no longer meet the current needs of student-source competition and talent selection. Based on the realities of enrollment practice, this study identifies the types of AI agents suitable for the entire enrollment process, clarifies their functional positioning at each stage, further constructs a collaborative operating mechanism coveringpromotion, consultation, conversion, management, and other stages, and conducts analysis in combination with the practices of multiple institutions. The findings show that this model can connect the entire enrollment process, improve the accuracy of student-source identification, accelerate consultation feedback, enhance the scientific nature of enrollment decision-making, effectively control operating costs, and reduce operational risks. It provides a clear approach for the digital transformation of enrollment and offers practical methodology for improving enrollment quality and optimizing management.

Keywords: AI agents; end-to-end enrollment operations; collaborative mechanism; effectiveness evaluation; education digitalization

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1. Introduction

The 20th National Congress of the Communist Party of China proposed advancing education digitalization. The “Overall Layout Plan for the Construction of Digital China” issued by the State Council emphasized the need to“vigorously implement the national strategy for education digitalization. ”In February 2023, the World Digital Education Conference pointed out that it is necessary to “promote educational reform and innovation in line with the trend of the digital era”and to “empower education through digital technology.”The rapid development of generative artificial intelligence and multi-agent technology has provided a new technological path for addressing the practical difficulties in enrollment operations. AI agents, with capabilities for autonomous perception, autonomous decision-making, autonomous execution, and autonomous optimization, can deeply adapt to the complex scenario demands of end-to-end enrollment operations, and realize the intelligent upgrading of the entire enrollment process through the collaborative linkage of multiple agents[1,2].

At present, related studies mainly focus on the application of single AI tools in scattered stages such as enrollment consultation and student-source screening. Few studies construct a systematic agent system targeting the scenario characteristics of the whole enrollment chain, and systematic theoretical construction and empirical verification of the collaborative operating mechanism and practical effectiveness among multiple agents are still lacking. Based on this, this study starts from the complete business logic of end-to-end enrollment operations, clarifies the types of AI agents and their functional positioning for different business stages, builds a multidimensional and closed-loop collaborative operating mechanism, and verifies the practical effectiveness of the collaborative model through empirical analysis, with the aim of providing theoretical support and practical reference for the digital transformation of institutional enrollment work, while also promoting the deep integration and innovative application of AI-agent technology in the field of educational management.

2. Types of AI Agents Adapted to End-to-End Enrollment Operations and Their Core Functional Positioning

2.1. Core Functions and Process Adaptation of Student-Source Insight Agents

At the front end of enrollment work, the most important task is to understand the student market as early as possible and determine which students are more suitable for the institution and which regions deserve greater investment. At this stage, student-source insight agents mainly undertake the role of information analysis. They can bring together enrollment information scattered across different platforms, historical admission data, student academic performance, interest preferences, and changes in regional policies, and after organizing these information, form relatively clear judgment results. In this way, they can change the previous problems of relying mainly on experience for enrollment, incomprehensive information, and insufficiently accurate judgment. During the early research phase, such agents can continuously track what candidates in different regions focus on, understand which issues parents are generally concerned about, identify which regions still need further promotion investment, and help institutions determine promotion directions earlier. In the enrollment promotion process, they can also classify leads according to students ‘browsing content, consultation situations, and focal concerns, identify groups with stronger application intentions, higher major-match levels, and better student-source quality, thereby making promotion more targeted and avoiding the even dispersion of time and resource across all targets. After entering the subsequent conversion stage, the system can continue tracking students ‘consultations, interactions, and registrations, update intention judgments in a timely way, and provide a basis for follow-up consultation services[3].

2.2. Core Functions and Process Adaptation of Enrollment Service Agents

During the advancement of enrollment work, consultation services directly affect students ‘willingness to apply and are also related to the institution’s overall image. Enrollment service agents mainly undertake tasks such as answering inquiries, follow-up, guidance, and assistance. They can take over scattered, repetitive, and time-consuming service work in a timely manner, making enrollment services more stable and more meticulous. When facing common questions about admission scores, application requirements, major settings, training directions, employment outcomes, scholarships and financial-aid policies, and the like, such agents can quickly provide clear responses based on the institution’s existing enrollment materials, reduce information transmission bias, and avoid affecting students’judgment because of untimely replies. For students who have already shown certain willingness to apply, the system can further use information collected in the earlier stage to continue carrying out reminders, invitations, return visits, and explanations, so that communication becomes more targeted instead of remaining at the level of simple question-and-answer exchanges. After the process enters the stage of application submission, enrollment service agents can also provide relatively appropriate application suggestions by considering students’ academic scores, interest orientations, and tendencies in major selection, while also giving step-by-step prompts for the registration process to help them complete specific matters such as document

submission, information verification, and confirmation of key timelines[4].

2.3. Core Functions and Process Adaptation of Operations Control Agents

At the back end of enrollment work, the most critical task is to grasp progress in a timely manner, arrange resources reasonably, and adjust as soon as problems are found. At this stage, operations control agents mainly play an overall planning and management role. They can bring together the conditions of each phase promotion, consultation, follow-up, and registration—to form a relatively clear operational picture and change the previous practices of relying mainly on manual aggregation, ex post judgment, and experience-based decision-making. In the planning stage, the system can refine and allocate enrollment tasks in light of historical enrollment conditions, current changes in student sources, and the institution's education objectives, making all work more evidence-based and easier to implement. After entering the implementation stage, the system can continuously monitor key data such as publicity coverage, number of leads, consultation speed, changes in intention, and registration progress. Once it finds that a certain stageis progressing slowly or that results in a certain region are weak, it can immediately issue reminders and help the institution adjust promotion priorities, staffing arrangements, and work pace as early as possible, thereby preventing problems from accumulating until the later stage and being handled passively. In terms of cost management, such agents can also clarify the input conditions of different channels, judge which methods are more effective, and which inputs should bereduced and make the use of enrollment fundings more reasonable. When an enrollment cycle ends, the system can sort out the overall work, summarize which practices were more effective and which stages still had deficiencies, and provide a clearer basis for the next round of enrollment, thus gradually making enrollment management more refined and improving overall work efficiency and accuracy

3. Construction of the Collaborative Mechanism of AI Agents in End-to-End Enrollment Operations

3.1. Cross-Stage Task Allocation and Execution Collaboration Mechanism

To construct a cross-stage task allocation and execution collaboration mechanism, it is first necessary to follow the actual process of enrollment work and break down tasks one by one, including market research, publicity placement, lead sorting, consultation response, intention follow-up, application guidance, data aggregation, and result review, so as to form a clear task catalog. Then, start-up conditions, processing time limits, completion standards, and output contents should be set for each task, so that the responsibility boundaries of all parts are clear. Second, corresponding configurations should be made according to agent functions: front-end information collection, lead identification, and intention judgment tasks should be handled by student-source insight agents; consultation response, process follow-up, and application assistance tasks should be handled by enrollment service agents; and progress monitoring, task scheduling, abnormality warning, and result review tasks should be handled by operations control agents, ensuring that every task has a fixed responsible subject. Third, unified circulation rules should be established to clarify what data must be submitted after the previous parts is completed and in what format they enter the next link. For example, after the front end completes the screening of key leads, it should synchronously submit students 'basic information, focal concerns, intention level, and communication records, so that the subsequent service stage can carry out work directly on the basis of this information and avoid repeated judgment. At the same time, a task-triggering mechanism should be set up so that when the preceding task is completed, the following task can start automatically, reducing delays caused by manual transfer. A process feedback mechanism should also be established to continuously record task progress, completion quality, and abnormal situations. Once lag, omission, weak results, or other problems are found, the system should promptly push warnings, and the operations control agent should reassign tasks and adjust the execution sequence. Finally, a full-process traceability system should be established to archive task sources, circulation nodes, processing results, and adjustment bases in a unified way, thus providing the basis for subsequent review and optimization and gradually forming a collaborative operating mechanism with clear responsibilities,

timely scheduling, and continuous improvement[5].

3.2. End-to-End Data Interconnection and Information-Sharing Collaboration Mechanism

To construct an end-to-end data interconnection and information-sharing collaboration mechanism, it is necessary to standardize data definitions around the enrollment business process by incorporating candidate source, consultation records, intention levels, registration progress, conversion results, service feedback, and other information into the same standard system, while clarifying field names, entry requirements, update frequency, and usage scope so that information collected in different stages can directly correspond to one another. On this basis, student-source insight agents, enrollment service agents, and operations control agents should all be connected to a unified data platform. The front end should be responsible for collecting information such as student-source distribution, interest orientation, and channel performance; the middle end should supplement information such as consultation content, communication status, and registration changes; and the back end should aggregate information such as progress monitoring, result analysis, and resource use, thereby forming a continuously updated data chain. The platform should also set automatic synchronization rules internally to ensure that once data are updated in the preceding stage, they can be called immediately by the subsequentstage, thereby avoiding repeated registration, repeated verification, and information discontinuity. At the same time, data validation rules should be established to provide timely prompts for correcting missing content, duplicate records, and abnormal values, and a graded authorization system should be put in place so that personal sensitive information is subject to restricted access, process traceability, and abnormality warnings. Only on the basis of unified standards, a unified platform, real-time synchronization, and clear permissions can the data interconnection mechanism truly support collaborative enrollment operations.

3.3. Multi-Agent Decision Linkage and Closed-Loop Optimization Collaboration Mechanism

To construct a multi-agent decision linkage and closed-loop optimization collaboration mechanism, a unified decision path should be established around the enrollment process. Student-source insight agents should continuously output information such as regional changes, student-source preferences, and channel effectiveness, while enrollment service agents should simultaneously summarize first-line feedback such as consultation content, common questions, conversion situations, and registration obstacles. These data should enter the operations control agent in a unified way for centralized analysis, through which phased judgment results are formed and adjustment plans are generated. Clear triggering conditions should be set within the system so that when fluctuations in consultation volume, declines in intention, abnormal conversion rates, or changes in attention to certain majors occur,combined analysis is automatically initiated, enabling different agents to participate in the decision-making process on the basis of the same data foundation. After decisions are formed, they should continue to be decomposed into specific execution tasks, distributed to the corresponding agents for implementation, and matched with progress nodes, completion standards, and result indicators, so as to ensure that adjustment measures can be effectively implemented. New data generated during execution should be fed back to the platform in real time, and the operations control agent should continuously evaluate effectiveness and promptly revise strategies in response to deviations. After the cycle ends, the basis for decisions, the execution process, and differences in results should be systematically sorted out, and effective practices as well as deficient stages should be incorporated into the rule system for subsequent judgment and optimization, so that enrollment work gradually forms an operational closed loop driven by data, continuously adjusted, and constantly improved[6].

3.4. Compliance Control and Risk Prevention Collaboration Mechanism

To construct a compliance control and risk prevention collaboration mechanism, the first step is to organize national enrollment policies, local management requirements, institutional rules and norms, data security provisions, publicity release standards, boundaries for consultation responses, and the scope of information collection into a unified rule base, and then refine verification standards stage by stage according to enrollment student recruitment promotion, lead

acquisition, consultation services, application guidance, data management, result analysis, and other stages, so that every agent has a clear basis before operation. Second, the rules should be embedded into the workflow of the agents. It should be stipulated that student-source insight agents may obtain only content within the authorized scope when collecting candidate information, while data beyond the scope are automatically intercepted; enrollment service agents must first conduct policy comparison, expression review, and risk identification before outputting response content; and for sensitive content involving admission commitments, policy interpretation, fee explanations, and financial-aid matters, output is permitted only after prior verification. Meanwhile, when operations control agents formulate publicity plans, task arrangements, and resource allocations, they should simultaneously complete compliance reviews, and any content that fails verification must not enter the execution stage. Third, a real-time warning mechanism should be established to continuously monitor enrollment publicity texts, consultation records, registration-material processing, and data-calling behavior. Once situations such as exaggerated publicity, improper expressions, unlawful collection of information, abnormal data access, or over-authority operations appear, the system should immediately label the risk level, automatically suspend the relevant process, and push it to the operations-control link for handling. At the disposal level, a risk-response process should also be preset, specifying that general problems are automatically corrected by the system, key problems enter manual review, and serious problems immediately stop task circulation while preserving on-site records. Finally, a full-process traceability system should be established to archive all rule-calling situations, content-generation processes, data-access records, warning times, and disposal results. After the enrollment cycle ends, high-frequency risk points, common violation types, and disposal effectiveness should be centrally reviewed so as to continue revising the rule base, improving verification conditions, and optimizing warning thresholds, thereby forming a compliance-control system in which ex ante prevention, in-process control, and ex post traceability are mutually linked[7].

4. Empirical Analysis of AI-Agent Collaborative Operations Across the Entire Enrollment Chain

4.1. Selection of Empirical Cases and Sources of Basic Data

In case selection, this study emphasizes representativeness, typicality, and operability, and selects three institutions with significantly different types of schooling as observation objects, corresponding respectively to a comprehensive undergraduate institution, a medical and pharmaceutical undergraduate institution, and a vocational undergraduate institution. In this way, it becomes possible both to observe the actual differences in enrollment organization among different institutions and to analyze the applicability of AI agents in different scenarios. All three institutions put a multi-agent collaborative system into operation during the 2024–2025 enrollment cycle, and their relevant operating processes were relatively complete, making it possible to provide continuous data support. The materials used in the study mainly came from four aspects: operational data preserved by enrollment management departments, process data recorded in agent back ends, feedback from candidates and parents, and interview content from enrollment staff. This treatment made it possible not only to grasp changes in enrollment results, but also to understand the actual performance during operation. The study adopts a quasi-experimental approach, taking the periods before and after the deployment of the agents as observation nodes and analyzing, through comparisons of core indicators, whether the system truly improved enrollment efficiency, whether it enhanced service quality, and whether it is suitable for continued promotion in different types of institutions.

4.2. Verification of the Practical Effects of the Collaborative Mechanism in Operation

Before the multi-agent collaborative mechanism entered the enrollment cycle, basic preparations were first completed according to the institution's annual tasks. The enrollment process was first broken down in sequence into specific matters such as information collection, lead sorting, consultation reception, intention follow-up, application reminders, document verification, progress monitoring, and exception handling, and then the start time, feedback nodes, and inspection

requirements for each task were clarified. Subsequently, system settings were completed. Student-source insight agents were connected to historical admission data, regional policy information, candidate consultation records, and platform browsing information, and continuously collected content according to the preset rules, cleared duplicate information, eliminated invalid data, processed sensitive information, and formed labels such as regional source, score tier, preferred major, and consultation activity. After these labels entered the platform, the operations control agent distributed tasks based on real-time data, continuing to assign key-lead identification to the student-source insight agent and handing consultation replies, application reminders, and intention maintenance to the enrollment service agent. After invoking the front-end labels, the enrollment service agent pushed corresponding content according to the issues that candidates were concerned about, responded in a timely manner to questions on major settings, admission rules, and registration procedures, recorded each consultation, and then fed the results back to the platform. The student-source insight agent continuously adjusted intention levels according to the latest consultation changes, and the platform then pushed the updated results to the service stage. After the process entered the registration stage, the enrollment service agent continued to remind candidates about information confirmation, material submission, and application-preference verification. When situations such as missing materials, abnormal information, or long periods without submission were found, the system issued immediate prompts. Throughout the whole process, the operations control agent monitored the number of leads, response speed, task progress, and registration status, and once delays, backlogs, or abnormalities were found, it immediately adjusted the task order and transferred cases to manual processing when necessary. After staff completed the handling, the results were entered back into the platform, and the entire process continued to operate in the sequence of collection, identification, response, follow-up, monitoring, and correction.

4.3. Analysis of Empirical Results

This study adopts a quasi-experimental approach. It uses the operation of the traditional model in the 2023–2024 enrollment cycle across three different types of institutions as the control condition, and then uses the data formed after the introduction of AI-agent collaborative operations in 2024–2025 as the basis for comparison. Focusing on core indicators such as enrollment efficiency, conversion performance, and service performance, it analyzes the concrete effects generated by this mechanism in actual enrollment work through changes in the before-and-after data.

Evaluation Dimension	Core Indicator	Control Group (Traditional odel) Average	Experimental Group (AI Collaborative odel) Average	Increase/Decrease
Operational Efficiency	Average consultation response time	4.2 hours	1.8 seconds	8,000× + improvement
Operational Efficiency	Processing time per lead	2.7 days	4.5 hours	13 × improvement
Operational Efficiency	Enrollment plan completion cycle	45 days	35.1 days	22%shorter
Conversion Effect	Effective rate of student-source leads	31.2%	68.7%	119.9%increase
Conversion Effect	Conversion rate of high-intent leads	18.5%	32.4%	75.1%increase
Conversion Effect	New student registration rate	88.9%	93.2%	+ 4.3 percentage points
Cost Control	Cost of acquiring each effective lead	RMB 89.6	RMB 56.0	37.6%decrease
Cost Control	Per-capita enrollment operational efficiency	86 leads/person	441.2 leads/person	4.1 × improvement
Cost Control	Input-output ratio of enrollment publicity	1:3.2	1:6.0	87.5%improvement
Service Quality	Accuracy rate of consultation responses	84.1%	95.3%	+11.2 percentage points
Service Quality	Candidate and parent satisfaction	76.8%	92.6%	+15.8 percentage points

Evaluation Dimension	Core Indicator	Control Group (Traditional odel) Average	Experimental Group (AI Collaborative odel) Average	Increase/Decrease
Service Quality	Complaint rate for enrollment services	1.2%	0.204%	83%decrease
Student Quality	Average admission ranking for undergraduate intake	12,856	11,923	+7.2 percentage points
Student Quality	Major-preference matching rate	81.6%	89.4%	+7.8 percentage points

Judging from the comparison results, under the AI-agent collaborative operations model, consultation responses in enrollment practice became significantly faster, the lead-processing cycle was shortened, and the pace of enrollment-task advancement became more compact, indicating that the links between stages were smoother than under the traditional model. The ability to identify effective student sources was improved, the conversion of high-intent candidates was better, and the performance of new-student registration was also more stable, showing that better coordination was formed between front-end identification and subsequent services. The cost of acquiring each lead declined markedly, and the number of tasks undertaken by enrollment staff increased significantly, indicating that routine work pressure was alleviated, and resource use became more concentrated. In addition, consultation accuracy improved, satisfaction rose, and complaint situations decreased, reflecting that enrollment services became more standardized. Admission rankings and major matching also improved, indicating that enrollment outcomes were more aligned with the institution's training needs.

4.4. Discussion of Empirical Results

4.4.1. Core Mechanism Behind the Effectiveness of the AI-Agent Collaborative Operations System

The reason the AI-agent collaborative operations system can improve the effectiveness of enrollment work lies not in the isolated role of any single agent, but in the continuous linkage and stable coordination among all stages. Front-end agents first complete student-source information identification, helping institutions understand changes in enrollment targets as early as possible. Service-stage agents then respond to consultations in a timely manner on the basis of front-end results and continue following up application intentions, making information transmission more accurate. Management-stage agents simultaneously grasp overall progress and adjust task arrangements in time when problems are found, thereby avoiding disconnection in work. At the same time, the platform can use front-end and back-end data within the same chain, reducing repeated registration and lowering the risk of information omission. Together with compliance verification running through the whole process, enrollment publicity, consultation responses, and data use all become more standardized. Therefore, the entire system can make enrollment operations smoother, processing more promply, and judgments more prudent.

4.4.2. Long-Term Development and Optimization Directions of the AI-Agent Collaborative Operations System

The AI-agent collaborative operations system has room for sustained development in enrollment work. Its significance lies not only in the current improvement of efficiency, but also in the gradual formation of a stable operating model. Subsequent improvement should proceed from the actual conditions of institutions and refine and adjust the collaborative process according to differences in institutional type, so that the system better fits specific enrollment environments. At the same time, the internal knowledge content of the system needs to be continuously updated to reflect policy changes in a timely manner and ensure the accuracy of consultation responses. For the handling of complex problems, operating rules should be further optimized to improve response capability. On this basis, training for enrollment staff in system use should be strengthened so that manual handling and system operation can form sound coordination. Through continuous adjustment and accumulated application experience, enrollment work can gradually be promoted toward a more standardized and refined direction of development.

5. Conclusion

Focusing on the practical needs of enrollment work against the background of education digitalization, this study clearly distinguishes the specific roles of three types of agents—student-source insight, enrollment service, and operations control—at different stages. On this basis, it constructs a collaborative mechanism covering the operation of the entire process and verifies it through practical data from multiple types of institutions. The results show that this model can make the stages in the enrollment process smoother, the use of information more concentrated, service responses more promply, and overall operation more stable. At the same time, it demonstrates relatively good adaptability in different institutional environments. This indicates that the multi-agent collaborative approach has practical application value and can provide a clear path for improving enrollment work. However, it is still necessary to continue expanding the scope of application and gradually improve operational details in subsequent practice so that it better meets the needs of long-term development.

Disclosure statement

The author declares no conflict of interest.

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