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From Monologue to Symphony: A Collaborative Framework for Fusion of ARCS-V Motivation Model and Multi-Agent Systems

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Abstract

In light of recent changes to engineering education, one of the primary issues facing vocational universities is how to effectively encourage and maintain the learning motivation of students. Lack of interest, low self-esteem, and weak willpower are common factors contributing to a lack of systematic motivation among students, especially in the technology-intensive and practical courses. Most existing instructional systems are limited in their ability to foster collaborative social learning and higher-order cognitive skills because of their "monologue" interaction paradigm and dependence on single-agent assistance. To address this challenge, this paper explores how to construct a collaborative teaching framework that combines the ARCS-V motivation model with an advanced multi-agent system. The framework seeks to establish an ecosystem that can methodically stimulate and sustain students' attention, relevance, confidence, satisfaction, and volition by establishing multi-role agents like experts, mentors, and peers. Quasi-experimental research method was adopted to compare the effect of multi-agent learning environment with traditional teaching mode. The results show that multi-agent environment can significantly improve students' learning motivation, and their academic performance in high-order cognitive dimensions such as reasoning and application is better, which effectively promotes deep learning cognitive level. This collaborative framework leverages advanced AI to establish a theoretical framework for methodically addressing learning motivation challenges and developing the advanced skills required by future applied professionals.

Keywords: multi-agent system, ARCS-V motivation model, vocational undergraduate education, instructional design

1. Introduction

Advances in large language models, exemplified by ChatGPT, have enabled sophisticated intelligent agents capable of multimodal, real-time interaction (text, image, audio and video), offering efficient feedback for learners [1,2]. Despite this, most educational applications still adopt a single-agent, question–feedback paradigm. While such systems provide some personalized support, they inadequately promote deep cognitive development and collaborative inquiry[3]. Multi-agent systems (MAS), by simulating a micro-society of interacting agents, offer richer, more dynamic learning environments that better support deep learning and address motivation systematically[4,5].

However, the popularity of technology does not automatically translate into improved academic learning. An important challenge in education remains: How to effectively motivate and sustain intrinsic academic motivation? A crucial idea in human behavior, learning motivation affects how well students learn and how teachers support their learning. Nonetheless, the issue of students' lack of motivation to learn is pervasive in today's educational practices. For instance, students in vocational education frequently lack motivation to learn and basic knowledge, which leads to low classroom participation[6,7].

These phenomena demonstrate how difficult it is to solve the deep learning conundrum by focusing solely on sophisticated technical tools while neglecting students' innate motivation needs. Therefore, the main problem that needs to be resolved immediately in the current education reform is creating a scientific and methodical framework for motivation design and thoroughly integrating it with state-of-the-art technology. Research on the learning motivation of vocational university students is currently scarce, and research on multi-agent based on large model driving is even scarcer. It is of great theoretical significance to explore how to stimulate vocational university students' learning motivation scientifically and effectively, and it also has positive practical guidance value for teaching practice.

In order to effectively stimulate and sustain students' deep learning motivation, this study aims to investigate a collaborative framework that can deeply integrate advanced multi-agent technology with systematic motivation design theory. This paper specifically seeks to address the following fundamental research question: How can instructional motivation design theory and cutting-edge multi-agent technology be methodically combined to produce a cooperative framework that effectively fosters and maintains students' deep learning motivation?

This thesis is organized as follows: The ARCS-V motivational design model and the educational agents' technological evolution trajectory from single to multiple agents are covered in Chapter 2. The main contribution of this thesis is presented in Chapter 3: A cooperative framework that combines multi-agent systems with the ARCS-V model. Chapter 4 will verify the effectiveness of this framework through an empirical case of "intelligent campus service robot". The work is summarized, and future research plans are outlined in Chapter 5.

2. Literature Review and Theoretical Foundation

2.1 The Use of Single-Agent and Multi-Agent Technology in Education

An agent—an intelligent entity capable of perceiving the environment, making decisions, acting, and learning autonomously—has historically been constrained by limited intelligence [8]. Recent advances in large models have strengthened agent capabilities. For example, Fiore et al. integrated ChatGPT as a single agent in software engineering education, using human–computer dialogue to guide students in critically evaluating the agent's solutions and iterating responses [9]. Their results indicate that this single-agent approach improves students' evaluative skills and creates a more engaging learning environment.

Nevertheless, single agents exhibit limitations that hinder deep learning and higher-order cognitive development. First, in complex, multi-task, multi-role scenarios, single agents lack flexibility and dynamic adaptability; their feedback tends to be narrow, and they cannot easily generate improved solutions through cooperation [10]. Second, a single-intelligence system is inadequate for stimulating higher-order thinking, which typically emerges in open-ended, multi-perspective problems [11]. Third, the "standard-answer" interactions common to single agents poorly foster reflection, questioning, and creative exploration. Fourth, the social component that maintains motivation and perseverance through peer support is eliminated in single-agent contexts, making learning essentially individual and isolated [12].

Multi-Agent Systems (MAS) represent a paradigm shift from agent-as-tool to agent-as-ecology. Rather than simply aggregating agents, MAS constructs a micro-society of autonomous agents with diverse roles, goals, and behaviors to address single-agent shortcomings [13]. MAS can simulate authentic social learning environments by including roles such as "experts," "mentors," "assistants," and "learners," thereby transforming student activity from human–computer interaction to social interaction [14]. Besides, through agent interaction and cooperation, MAS can produce emergent group intelligence ("1+1>2"), yielding more accurate and complete feedback and reducing misleading "illusion" effects [15]. Crucially, MAS changes tasks from seeking a single correct answer to collaborative problem solving: students may work with peer agents, consult expert agents, and critique their recommendations, or persuade agents holding different views. Zhai et al. found that participation in such multi-agent social-cognitive activities significantly enhanced students' higher-order abilities—reasoning, evaluation, and application—thereby promoting deep learning [16].

2.2 ARCS-V Motivation Model

The ARCS-V model, proposed by Keller, synthesizes classical motivation theories to guide instructional design by sequentially stimulating interest, establishing relevance and value, building confidence, and providing satisfaction [17]. ARCS denotes Attention, Relevance, Confidence, and Satisfaction; the added V (Volition) emphasizes students' self-regulation [18, 19].

ARCS-V has been widely and successfully applied in engineering and technology courses due to its theoretical coherence and practical operability. Empirical studies validate its effectiveness in motivating students in complex, abstract, and practice-oriented courses and inform the present study's framework. For example, in software and algorithm courses, Li et al. combined ARCS-V with project-based learning (PBL) in a face-recognition classroom-attendance project: creating engaging scenarios (Attention), using familiar faces (Relevance), offering algorithms of varying difficulty (Confidence), and delivering functional demonstrations (Satisfaction), which enhanced motivation and deep understanding [20]. In foundational courses like Mechanical Drawing, Wang et al. applied ARCS strategies—interesting cases and multimedia to capture attention, linking content to professional needs for relevance, building confidence via a “success ladder” (clear goals, group work, timely feedback), and increasing satisfaction through positive feedback [21].

In summary, ARCS-V consistently stimulates student motivation and improves learning outcomes [22], and it suits technology-supported instructional design [23]. Therefore, integrating Multi-Agent Systems with the ARCS framework can combine technical affordances and instructional design strengths to further promote students’ deep learning.

3. ARCS-V and Multi-Agent Collaborative Framework Design

3.1 Motivational Needs and Agent Mapping Dimensions

The core theoretical contribution of this study is to construct a collaborative framework that systematically maps the five dimensions of the ARCS-V motivation model to the unique functions of MAS. The fundamental idea is that ARCS-V models identify students’ motivational needs at various stages (“what needs”), and MAS offer strong capabilities to satisfy these needs (“what can be done”). This framework aims to show that MAS can not only implement traditional ARCS-V strategies but also enrich and enhance them with depth, breadth, and dynamics that single agents cannot, resulting in an intrinsic and long-lasting incentive loop.

3.2 A Collaborative Implementation Path for Each Dimension of The ARCS-V Model

Each of the ARCS-V model's dimensions will be examined individually in this section, along with an explanation of how a multi-agent system's capacity for cooperation can enhance the corresponding motivation strategy.

3.2.1 Dimension of Attention

(1) Single-agent limitations. While a single agent can draw students’ attention by asking questions or changing the content, its change mode is limited, and the interactive object is always the same “it”. This makes it difficult to sustain students’ attention over the long term and can quickly cause aesthetic fatigue and habituation.

(2) Multi-agent collaborative path design. MAS fundamentally address the issue of diversity by introducing multiple agents with distinct personalities, roles, and interactions. We can create a full narrative scenario for teaching activities: first, a rigorous “expert” agent poses an inquiry heuristic problem; next, a lively “student partner” agent encourages students to work together to solve it in a relaxed language and introduces new problem-solving tools, thereby expanding the variety of instruction; and finally, a mentor agent can use immersive virtual simulation animation to visually illustrate and introduce the problem’s background knowledge. Compared to the linear interaction of a single agent, this type of teaching scenario, which is deduced by multiple actors and develops dynamically, draws and holds attention much longer.

3.2.2 Dimension of Relevance

(1) Single-agent limitations. It can only convey to students that “this knowledge is very important” in a didactic, one-way manner, and it is challenging for them to genuinely make the connection between knowledge and their personal lives.

(2) Multi-agent collaborative path design. MAS can construct a multidimensional correlation network through role-playing. A “mentor” agent can match abstract knowledge points with students’ personal goals and future development paths like a career planner; a “companion” agent can share its learning experiences and puzzles, explain concepts with peers’ perspectives and life examples, and thus establish a strong sense of familiarity and intimacy. In order to achieve a deep level of goal orientation, the system can also introduce a simulated “industry expert” or “enterprise HR” agent, issue a simulated real project requirement, and allow students to intuitively feel the application value of the learned knowledge in the future career scenario.

3.2.3 Dimension of Confidence

(1) Single-agent Limitations. In the face of actual challenges, it can only offer linear, predetermined scaffolding support and has limited capacity to handle students’ complex and variable emotional and cognitive barriers.

(2) Multi-agent collaborative path design. MAS can build a three-dimensional social support system to foster student confidence. Specifically, a “teaching assistant” agent can be designed to dynamically provide layered tasks

and immediate "scaffolding" tools based on students' real-time performance, creating ample opportunities for students to succeed. It is also possible to design a "companion" agent to fight alongside students and explore difficult problems together. This feeling of companion can effectively share the cognitive load of students and significantly reduce the frustration caused by fighting alone. In addition, when students fail, designing an opinion-neutral "real-time correction" or "reflection" agent can guide them to make positive personal control attributions and help them analyze whether the failure is due to improper strategy or knowledge gap, rather than due to their own lack of ability, thus protecting and rebuilding their learning confidence.

3.2.4 Dimension of Satisfaction

(1) Single-agent limitation: The reward and feedback mechanisms of a single agent are usually singular and limited in form.

(2) Multi-agent collaborative path design: MAS can provide richer and more diverse sources of satisfaction. Students' internal reinforcement feelings no longer come from completing tasks alone but from a strong sense of team accomplishment and belonging after successfully collaborating with "peer" agents to solve difficult problems. In addition, external rewards have become diverse, such as personalized praise from "mentor" agents, digital certificates from "expert" agents, or likes from other members of "community" agents. A "referee" agent, which employs a variety of transparent criteria to assess the process based on objective data of the entire learning process, can also be introduced to guarantee fairness and make sure that every effort made by students is acknowledged.

3.2.5 Dimension of Volition

(1) Single-agent limitation: It is difficult to supervise students effectively for a long time, and it cannot provide complex emotional support to help them overcome learning burnout.

(2) Multi-agent collaborative path design: MAS can provide social support for willpower maintenance. Specifically, "mentor" agents can work with students to formulate, disassemble, and track learning goals, helping them translate learning intentions into concrete actions. When students encounter setbacks and frustrations in the long learning process, "peer" agents can actively intervene to provide emotional support and positive psychological cues to help them self-regulate. The entire multi-agent environment itself, through continuous task posting, team interaction, and progress reminders, constitutes a powerful external drive to help students effectively monitor themselves and prevent them from deviating from their learning trajectory.

3.3 The Collaborative Framework's Mapping Table and Teaching Design Cases

In order to more intuitively and systematically demonstrate the collaborative framework described in the previous section, the following table cross-maps the five dimensions of the ARCS-V model and their key sub-strategies with different role functions in MAS and provides specific teaching design cases for each intersection. This table is not only a concise summary of the core theory of this paper but also a practical tool that can directly guide instructional designers and AI system developers, aiming to transform abstract motivation theory into operational and technology-enabled instructional strategies.

Table 1. Collaborative Framework Mapping Table and Teaching Design Case

ARCS-V dimension	expert agent	assistant/mentor agent	peer agent
A- Attention	Propose profound inquiry heuristic questions that challenge students 'inherent perceptions.	Create engaging perceptual wake-up situations through multimedia and virtual simulations.	Introduce novel problem-solving ideas or initiate debates to increase the diversity of the teaching process.
R- Relevance	Elaborate on the deep connection between knowledge and cutting-edge science and technology, industry development, and embody goal orientation.	Break down learning goals and match motivation with students' personal development paths.	Share (simulated) learning experiences, explain abstract concepts with life examples, and build familiarity.
C- Confidence	Provide an authoritative and systematic knowledge system	Layered tasks and immediate scaffolding are provided to create ample	Work with learners to solve problems, share cognitive

	as reliable knowledge backing for learners to explore.	opportunities for students to succeed.	load, and reduce frustration through social support.
S-Satisfaction	Give high and authoritative affirmation to the profound insights or innovative solutions proposed by learners.	Give timely, personalized praise and encouragement as effective external rewards.	Celebrate the accomplishment of team tasks together, provide social recognition, and reinforce students' inner satisfaction.
V-Willpower	Set a long-term, challenging vision of learning that inspires students to pursue long-term goals.	Help students develop and track actionable learning plans that materialize abstract implementation intentions.	Encourage each other when learning bottlenecks, provide emotional support, and help students self-regulate.

4. Empirical Analysis

4.1 Project-Based Learning: The Role of Motivational Design in Complex Tasks

In order to verify the effectiveness of the collaborative framework proposed in this paper in the "new engineering" education practice, we designed and implemented a quasi-experimental study based on the core training module of service robot development. In order to investigate the practical effects of this mode on enhancing the deep learning capacity and high-order cognitive level of vocational college students, this study forgoes the conventional teacher-centered teaching mode and instead uses the project-based learning (PBL) method to deeply integrate the ARCS-V motivation model with multi-agent systems.

As the study's teaching case, we have selected the "Intelligent Campus Service Robot Programming and Debugging" project. This case was selected for two reasons: first, it is highly cutting-edge and life-related. Service robot is a hot field of integration of artificial intelligence and robot technology. It is widely used in navigation, distribution, assistant and other scenes, and is closely connected with students' daily life and future scientific and technological development trend. Second, the complexity of the task and the complexity of the technology stack. A complete service robot project needs to integrate robot operating system (ROS), simultaneous localization and mapping (SLAM) navigation algorithm, multi-sensor fusion obstacle avoidance technology and speech recognition, which provides an excellent carrier for the cultivation of high-level cognitive ability. The end result is an intelligent robotic entity that can move autonomously and interact with humans in a real environment, a process that is full of exploration, creativity, and a sense of accomplishment, and is ideal for systematic motivational design using ARCS-V models.

In the experimental design, the students of the experimental class will complete the project in a multi-agent learning environment composed of expert agent, mentor agent and peer agent. The control class adopts the traditional teaching mode, in which the teacher teaches ROS foundation, navigation, obstacle avoidance and other knowledge points in turn, then let the students practice comprehensively in groups, and finally submit the results. By comparing the performance of the two groups of students at the end of the project, this study aims to reveal the inherent advantages of the proposed fusion framework.

4.2 Analysis of Research Data

After a semester of teaching experiment, we analyzed the data from three dimensions: academic achievement, motivation and cognitive depth. The results of the study provide strong evidence for the superiority of multi-agent systems in promoting higher-order cognitive abilities.

4.2.1 Academic Performance Analysis

One-way analysis of covariance (ANCOVA) was performed on the final scores of the two groups (40% theoretical test and 60% project practice test): the pretest was taken as a covariate and the post-test as a dependent variable, which could make the comparison of posttest scores more fair and accurate. To further explore the sources of differences, we subdivide the project practice assessment into four dimensions: *literal understanding* (such as correct use of ROS basic instructions), *reasoning analysis* (such as planning optimal navigation strategies according to map environment), *evaluation* (such as evaluating the advantages and disadvantages of different obstacle avoidance algorithms and optimizing parameters) and *comprehensive application* (such as successfully integrating all modules and completing complete voice navigation tasks).

The results of one-way covariance analysis are shown in Table 2. After controlling for the influence of pretest scores, there is a significant difference between the experimental group and the control group in total scores ($F(1,79)=15.234$, $p<0.001$, $\eta^2=0.250$). Specifically, students in the experimental group performed significantly better than those in the control group in reasoning analysis($F(1,79)=16.543$, $p<0.001$, $\eta^2=0.280$), evaluation ($F(1,79)=18.765$, $p<0.001$, $\eta^2=0.300$) and comprehensive application ($F(1,79)=9.876$, $p<0.001$, $\eta^2=0.180$), but there was no significant difference in literal understanding ($F(1,79)=0.567$, $p > 0.05$), which indicated that traditional teaching could also effectively impart basic knowledge. This result confirms that motivational learning activities based on multi-agents can effectively improve students' overall academic performance and have significant effects on promoting the development of higher-order thinking ability.

Table 2. One-way covariance analysis of academic performance

variable	**group**	**number of students**	**mean value**	**standard deviation (SD)**	**adjusted mean**	**standard error (Std. Error)**	**F**	η^2
total score	experimental group	40	82	4.5	82.3	0.48	15.234*	0.25
	control group	41	80.5	4.2	80.23	0.47		
literal understanding	experimental group	40	29.1	2.6	29.05	0.28	0.567	0.01
	control group	41	29.25	2.4	29.29	0.27		
reasoning analysis	experimental group	40	22.5	2.1	22.55	0.22	16.543*	0.28
	control group	41	20.8	2.3	20.76	0.22		
evaluation	experimental group	40	16.2	1.8	16.25	0.19	18.765*	0.3
	control group	41	15	1.9	14.96	0.19		
comprehensive application	experimental group	40	8.2	1.05	8.15	0.11	9.876*	0.18
	control group	41	7.45	1.15	7.49	0.11		

Note: ***p<0.001

This result clearly shows that multi-agent environments, through their rich role interactions and collaborative tasks, can more effectively guide students beyond simple repetition of knowledge to deeper levels of analysis, judgment, and creative application. For example, in interaction with expert agents, students must evaluate the applicability of different navigation algorithms in specific scenarios; in collaboration with peer agents, they need to reason out the most efficient module integration scheme; and under the guidance of learning agents, they apply what they have learned to solve dynamic issues that are new and complicated.

4.2.2 Learning Motivation and Cognitive Depth Analysis

By analyzing ARCS-V scale before and after the experiment,taking the pretest as covariate and the post-test as dependent variable, the results showed that there were significant differences in learning motivation between the experimental group and the control group($F(1,79)=18.763$, $p<0.001$, $\eta^2=0.288$). The adjusted mean of the experimental group was 4.28 (SD=0.32), significantly higher than that of the control group was 3.55 (SD=0.41). This result confirms that multi-agent system can effectively stimulate students' intrinsic motivation through role simulation, such as personalized encouragement of guidance agent and cooperative encouragement of peer agent. The effect size $\eta^2=0.288$ (Cohen criterion: >0.14 large effect) further indicates that 28.8% the motivation variation of can be explained by multi-agent intervention, far exceeding the conventional threshold of 10% in educational technology research [24].

Table 3. One-way covariance analysis of learning motivation

group	number of students	mean value	standard deviation (SD)	adjusted mean	standard error (Std. Error)	F	η^2
experimental group	40	4.25	0.32	4.28	0.05	18.763*	0.288
control group	41	3.58	0.41	3.55	0.05		

Note: 1. Motivation scale uses Likert 5-point scale (1 = very inconsistent, 5 = very consistent); 2. * p<0.001

Furthermore, cognitive network analysis was performed on the interaction data (such as conversation records with agents, group discussion texts) of students during learning. The study found that the cognitive activities of the control group students stayed more in the "single-point structure" (such as asking for the use of a ROS instruction) and "multi-point structure"(such as listing multiple operation steps) related to shallow learning. The cognitive activities of the experimental group showed more "association structures" related to deep learning (such as discussing the impact of sensor data fusion on obstacle avoidance) and "abstract extension structures"(such as extending the navigation framework principles of this project to autonomous vehicles). This finding directly reveals the essential difference between the two technology paradigms in learning quality: one-way, instrumental technology application tends to guide students to memorize and list knowledge points, while the social learning ecology constructed by multi-agents can effectively promote students to associate, integrate and abstract knowledge, thus realizing true deep learning.

5. Summary and Outlook

This study systematically explores how to effectively address the core challenge of learner motivation in the context of the deep penetration of artificial intelligence technology into education. This study argues that solving the motivation problem requires a paradigm shift from a tool-oriented view of AI to an ecological view. Single-agent systems, regardless of their algorithmic sophistication, are inherently limited by "monologic" interaction patterns, which fail to meet the complex socio-cognitive demands of deep learning. Therefore, a collaborative framework integrating the ARCS-V motivation model and a MAS is constructed and demonstrated. At the heart of the framework is the use of MAS to simulate a dynamic, diverse, social-learning ecosystem. In this ecosystem, agents playing different roles (experts, mentors, peers, etc.) work collaboratively to integrate the five ARCS motivational strategies (attention, relevance, self-confidence, satisfaction, willpower) into the overall learning process in an intrinsic and contextual way. Empirical analysis and case studies show that this collaborative framework can stimulate and maintain deep learning motivation of learners more systematically and deeply than single agent system, and effectively promote the development of high-order cognitive abilities such as reasoning, evaluation and application. This study constructs and verifies the effectiveness of the collaborative framework and demonstrates its operability in real teaching environment.

The conclusions of this study have important implications for future educational practice and related research fields. (1) The role of teachers needs to undergo a profound transformation. They may no longer only be imparting knowledge but also become the designer, guide and coordinator of learning ecology. Future instructional design will focus on how to create meaningful, multi-agent complex problem situations and how to guide students to explore, collaborate and reflect effectively in such ecosystems. (2) For AI education system developers, the focus of research and development should shift from optimizing dialogue or recommendation algorithms for single agents to designing collaborative mechanisms, role-playing rules, and dynamic interaction logic between agents. ARCS motivation models should be viewed as top-level design principles for system architecture, not as "sugar coating" added afterwards. The success of the system will depend more on whether it can successfully construct a virtual society that can continuously stimulate and satisfy learners' motivation needs.

For future research, there are several directions worthy of further exploration: (1) Long-term effect research: Based on this framework, long-term empirical research is mostly short-term intervention, and longitudinal research is carried out to investigate the long-term impact of this framework on students' learning ability, motivation pattern, and career development. (2) Ethics and risk research: The social ecosystem composed of multiple agents may also bring new ethical risks, such as excessive emotional dependence of students on agents, strengthened prejudice in the "information cocoon room" composed of agents, and possible negative social behaviors (such as exclusion and deception) among agents. The identification, assessment, and avoidance strategies of these potential risks will be crucial research topics. (3) Innovation in evaluation methods: Traditional knowledge tests are no longer sufficient to evaluate students' abilities in complex human-computer collaborative ecosystems. New assessment methods and tools need to be developed to effectively measure learners' collaborative, critical, systematic, and innovative abilities in this environment.

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