*Perspective:*

# Large language model and domain-specific model collaboration for smart education[*]

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In this paper, we introduce the large language model and domain-specific model collaboration (LDMC) framework designed to enhance smart education. The LDMC framework leverages the comprehensive and versatile knowledge of large domain-general models, combines it with the specialized and disciplinary knowledge from small domain-specific models (DSMs), and incorporates pedagogy knowledge from learning theory models. This integration yields multiple knowledge representations, fostering personalized and adaptive educational experiences. We explore various applications of the LDMC framework in the context of smart education. LDMC represents an advanced and comprehensive educational assistance framework, enriched with intelligent capabilities. With the continuous advancement of artificial intelligence (AI), this framework is poised to offer promising potential in significantly impacting the field of smart education.

## 1 Introduction

The goals of modern education are to offer personalized, precise, and ubiquitous learning guidance or support to individual students based on their learning status, preferences, or personal characteristics (Hwang, 2014). Over the last 30 years, AI has been widely used in education since the advancement of natural language processing (NLP) techniques, creating new opportunities for designing productive learning activities and developing better learning applications.

### 1.1 Domain-specific models for smart education

Traditional educational techniques are characterized by their focus on specific knowledge domains and the accomplishment of singular educational tasks (Wang XH et al., 2022). For instance, the bag-of-words (BoW) models (Zhang Y et al., 2010) have been originally proposed for text classification, while the long short-term memory (LSTM) models (Greff et al., 2017) were designed to address language translation and text-based Q&A tasks. Additionally, knowledge graphs (KGs) (Shi et al., 2020) were employed to facilitate learning path recommendations and scientific retrieval processes. These small-scale domain-specific models offer several advantages, including well-defined knowledge boundaries, low computation costs, and improved interpretability. Their

practicality lies in their ability to provide clear delineations of subject matter, which is beneficial in educational contexts. Additionally, their efficient computational requirements make them accessible and suitable for various learning environments. Moreover, the enhanced interpretability of these models allows educators to gain deeper insights into the learning process, leading to improved pedagogical strategies. However, these small-scale domain-specific models have limitations. They can handle only straightforward and isolated tasks due to their limited training data scope and model structure. As a result, they lack robust reasoning abilities and the ability to produce human-like output.

## 1.2 Smart education using large language models

In more recent years, there has been significant progress in smart education with the emergence of large language models (LLMs) (Wang J et al., 2023; Zhou et al., 2023) like the pre-training of deep bidirectional encoder representations from Transformers (BERTs) and generative pre-trained Transformers (GPTs). These models have undergone training on extensive text datasets, enabling them to generate text that closely resembles human language, accurately answer questions, and perform a wide range of language-related tasks. In addition to training on vast amounts of text, the more recently proposed ChatGPT was further trained using reinforcement learning from human feedback (RLHF) (Griffith et al., 2013). In RLHF, humans manually tag the best responses produced by an initial language model to improve its performance at specific tasks. Through these repeated machine–human interactions, ChatGPT was trained to engage in dialog, be more truthful, and avoid inflammatory or offensive language. Researchers have also conducted extensive studies to fine-tune LLMs on smaller datasets and apply transfer learning to address specific domain-related problems. Consequently, these models have exhibited improved performance on targeted tasks, even in scenarios where the availability of data is limited.

Due to the promising performance of GPT-like LLMs, the integration of GPTs and similar language models in the realm of smart education has garnered considerable attention and sparked numerous research endeavors. Scholars and practitioners have concentrated their efforts on various domains, including intelligent tutoring systems (ITSs), adaptive learning platforms, and virtual assistants tailored to students' needs. By harnessing the unique capabilities of ChatGPT, these systems strive to provide learners with unparalleled individualized support, delivering custom explanations, addressing queries, and furnishing interactive learning materials. Moreover, researchers have endeavored to incorporate advanced techniques such as NLP and sentiment analysis to gauge student engagement levels and emotional states, enabling the provision of adaptive feedback and interventions accordingly. While there are still obstacles to surmount, the ongoing work in integrating ChatGPT within smart education holds immense promise in transforming traditional teaching and learning methodologies, fostering highly personalized and interactive educational experiences, and ultimately elevating educational outcomes for students to new heights. Note that in this study we mainly propose a new perspective on how to better use LLMs in real educational scenarios, rather than proposing new large model structures or fine-tuning techniques.

## 1.3 Learning style models

In addition to domain knowledge and learning tasks, modeling learners' learning habits is crucial in improving learning outcomes. Here we revisit several classic learning theory models.

### 1.3.1 Felder & Silverman model (Felder and Silverman, 1988)

This model suggests that individuals exhibit preferences across various learning styles: sensing vs. intuitive, visual vs. verbal, active vs. reflective, and sequential vs. global. Active learners engage best through hands-on activities, while reflective learners prefer contemplation and thinking about the learning material. Sensing learners rely on their senses to grasp concrete facts, while intuitive learners thrive with abstract concepts and their underlying meanings. Visual learners excel in remembering information presented visually, such as through images or diagrams, whereas verbal learners prefer textual representations in written or spoken form. Sequential learners follow a step-by-step learning approach, while global learners

grasp the big picture first through a holistic thought process.

### 1.3.2 Honey & Mumford model (Honey and Mumford, 1994)

This is a widely recognized framework that categorizes individuals into four distinct learning styles based on their preferences and approaches to learning. In this model learners can be classified as activists, reflectors, theorists, or pragmatists. Each learning style represents different ways of engaging with and processing information, indicating how individuals approach learning tasks and acquire knowledge. This model serves as a valuable tool for understanding individual learning preferences and designing effective learning experiences tailored to different learning styles.

### 1.3.3 Kolb's model (Healey and Jenkins, 2000)

This model is a comprehensive framework that explains how individuals learn through a four-stage process. The model highlights the significance of active experimentation and concrete experiences in the learning journey. The four stages are concrete experience, reflective observation, abstract conceptualization, and active experimentation. Effective learning occurs when individuals cyclically progress through these stages, continuously experiencing, reflecting, conceptualizing, and experimenting. This cyclical learning process enables learners to build on their knowledge and experiences, resulting in a deeper understanding and the acquisition of practical skills.

### 1.3.4 VARK model (Fleming and Baume, 2006)

This model classifies learning styles into four categories: visual, aural, read/write, and kinesthetic. Visual learners prefer visual knowledge like maps, charts, and graphs (Zhuang and Tang, 2021; Pan, 2022). Aural learners prefer information presented through listening or speaking, such as lectures or group discussions. Read/Write learners prefer text-based learning through reading and writing activities like manuals and essays. Kinesthetic learners prefer to require knowledge through experiments and hands-on activities, which can be virtual or in person, including demonstrations and case studies.

### 1.4 Discussion

A proliferation of benchmarks and tasks have been leveraged to evaluate the effectiveness and superiority of LLMs (Dai et al., 2023; Zhang XT et al., 2023). Results from corresponding experiments demonstrate that LLMs achieve much better performance than previous deep learning models and smaller DSMs on an array of NLP tasks. Besides, LLMs exhibit some emergent abilities and are capable of solving diverse complex tasks that traditional models cannot address. Nevertheless, LLMs have been found to encounter new challenges in educational tasks such as over-wide knowledge boundaries and frequent hallucinations. This gives us insight into the combination of LLMs and DSMs. The pros and cons of LLMs/DSMs in educational scenarios can be summarized as follows.

#### 1.4.1 Domain knowledge

Due to the scarcity of domain-specific corpora, LLMs may not exhibit the same level of performance on domain-specific tasks as they do on general ones. Tasks such as generating chemical equations, relying on a multitude of intricate chemical rules, can present significant challenges for LLMs. In contrast, DSMs can be designed and fine-tuned specifically for a particular domain, allowing them to focus on capturing the intricacies and domain-specific knowledge necessary for achieving higher performance.

#### 1.4.2 Human alignment

The outputs of DSMs typically adhere to predefined structures, exemplified by knowledge graphs that yield triplets as their primary output. In contrast, LLMs can undergo reinforcement learning and fine-tuning processes to generate anthropomorphic responses that not only conform to human values but also align closely with human expectations. This results in generated content that is notably more comprehensible to students. By harmonizing with human values and speech patterns, LLMs ensure that the information imparted to students is characterized by respect, inclusivity, and a notable absence of biased or harmful content. This attribute holds particular significance within educational contexts.

### 1.4.3 Knowledge boundary

The abundance of domain-general training data empowers LLMs to function as nearly omniscient tutors, boosting their ability to cope with more complex zero-shot and reasoning tasks. Nevertheless, the over-wide knowledge boundary can also present challenges in educational contexts. First, the generation of learning-independent content by LLMs may divert students' attention, leading to potential distractions from the intended learning objectives. Second, when LLMs generate content that surpasses the cognitive level of students, it can cause confusion and hinder effective comprehension. In contrast, DSMs offer more explicit delineations of knowledge boundaries and can better harness the learning procedure.

### 1.4.4 Knowledge obsolescence

This issue highlights a fundamental limitation of LLMs in their ability to keep pace with rapidly evolving domains: Pre-training on prior texts establishes a foundation of knowledge that is fixed at the time of training, rendering LLMs less capable of acquiring new information beyond their initial corpus. Considering their high training and fine-tuning costs, LLMs may struggle to provide accurate and up-to-date insights in fields where knowledge evolves quickly, such as investment principles. In contrast, DSMs can be trained and fine-tuned more quickly. By focusing on specific domains, these models can capture the nuances and intricacies of specialized knowledge, providing insights even in rapidly evolving disciplines.

Summary: The aforementioned LLMs and DSMs have their respective pros and cons. The leveraging of the complementary benefits of many types of knowledge having their origins in different models using human insight as a basis is a common approach in the design of machine learning programs capable of mimicking intelligent human activities such as learning and decision-making. This implies that model collaboration, which integrates multiple elements of educational knowledge via appropriate mechanisms, could be an option for advanced smart education.

## 2 LDMC framework

In this section, we present the LDMC framework (Fig. 1), aimed at enhancing educational assistance capabilities through the acquisition, representation,

and manipulation of educational knowledge from multi-level and multi-specialized models. The collaborative integration of large domain-general models, small domain-specific models, and pedagogy knowledge from learning theory models forms the basis of LDMC. This framework yields multiple knowledge representations (MKRs) (Pan, 2019; Yang et al., 2021, 2022) in the context of education and is tailored specifically to foster personalized, accurate, and adaptive educational experiences, addressing the diverse learning needs of students.

### 2.1 LDMC architecture

The LDMC framework combines the strengths of various models, enabling efficient and comprehensive support for educational tasks with MKR (Pan, 2020, 2021). By leveraging the extensive knowledge of large domain-general models, LDMC gains a versatile understanding of diverse subject matters. Simultaneously, the integration of specialized domain-specific models ensures that disciplinary knowledge is accurately represented and applied. Pedagogy knowledge from learning theory models further enhances the framework's adaptability and efficacy in accommodating individual learning styles and preferences.

### 2.2 Personalization and adaptation

One of the key features of LDMC is its ability to perform real-time updates to the style of study recorded in the framework's memory (Bajaj and Sharma, 2018; Reif et al., 2022). This adaptability allows the framework to cater to personalized study habits and accommodate learners adaptively in different stages and scenarios (Luo et al., 2019, 2022) of their educational journey. Specifically, the learning style, controlled by the weighted combination of the learning theory models, is updated based on the student's current learning state through a reward function. In this way, the weight for each learning style model (LSM) can be directly updated via gradient backpropagation within a reinforcement learning paradigm. By constantly evolving to match the changing needs of students, LDMC provides an enhanced and engaging learning experience.
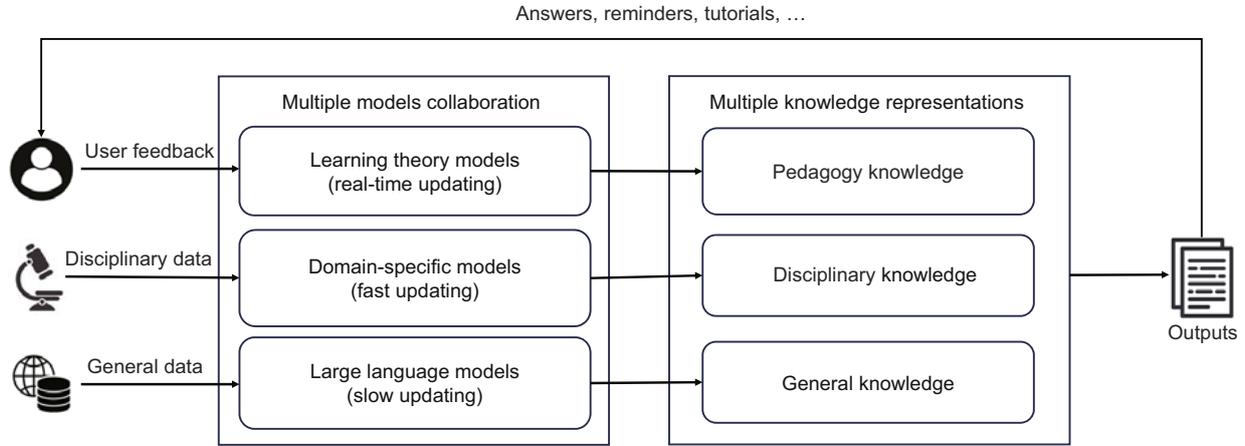
Answers, reminders, tutorials, …



**Fig. 1  Large language model and domain-specific model collaboration (LDMC) framework**

## 2.3  Timely updates for knowledge freshness

The fast updates of DSMs prevent disciplinary knowledge from becoming obsolete, ensuring that the framework remains current with the latest developments in various subject domains. In contrast, the pre-trained LLMs undergo slower updates due to the substantial training cost associated with them. This balanced approach ensures that LDMC maintains its efficiency without sacrificing accuracy. DSMs are updated only if there are significant changes to the course content or if the model is applied to another course. In practice, we use learning with optimized random auxiliary tasks (LoRa) again to refresh the injected knowledge in LDMC and update the KG to guarantee an up-to-date knowledge supplementation and constraint.

## 2.4  Implications and extensions

The proposed LDMC framework carries several implications for educational technology. Its ability to synergize diverse models not only fosters personalized learning but also opens avenues for advanced educational applications. The characteristics of LDMC provide potential extensions in the form of tailor-made educational tools, catering to specific domains or unique learner profiles.

## 2.5  Cooperative modes of LLMs and DSMs

We proposed three cooperative modes of LLMs and DSMs: knowledge injection, knowledge supplementation, and knowledge constraint (Fig. 2).
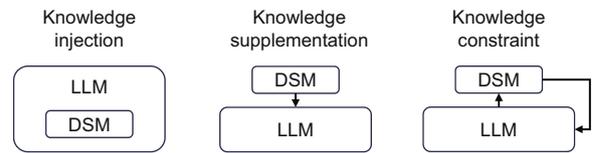


**Fig. 2  Cooperative modes of large language models (LLMs) and domain-specific models (DSMs)**

Knowledge injection: In the knowledge injection mode, DSMs are seamlessly integrated into LLMs as lightweight learning modules. The process involves fine-tuning LLMs using discipline-specific data, wherein all weights remain fixed except for those associated with DSMs. One approach involves incorporating task-specific adapter layers (Seo et al., 2023), while there are other techniques, such as prompting (Zamfirescu-Pereira et al., 2023), which obviate the need for fine-tuning model parameters. In this context, DSMs play a crucial role in generating learnable prompts, thereby significantly enhancing the in-context learning capability of LLMs. Moreover, a novel methodology named LoRa (Hu et al., 2021) has been introduced, driven by the insight that pre-trained LLMs typically possess low "intrinsic dimensions." Through LoRa, discipline-specific knowledge is efficiently injected into re-trained LLMs, resulting in a commendable balance between time cost and memory footprint. Overall, this knowledge injection mode presents a powerful and pragmatic approach for augmenting LLMs with discipline-specific knowledge, empowering them to excel in various context-based learning tasks while efficiently using computational resources.

Knowledge supplementation: In this collaboration mode, DSMs play a crucial role as external disciplinary knowledge complementors for LLMs, effectively mitigating their tendencies toward hallucination when dealing with professional queries or intricate relationships (Agarwal et al., 2021). Taking KGs as an example, to facilitate the seamless combination of structured KGs and unstructured LLMs, we initiate the process by extracting language queries and transforming them into entity subgraphs through relation pair alignment. Subsequently, the responded subgraph triples are converted into natural language text, yielding coherent answers that align closely with domain-specific facts. In this mode, the utilization of structured knowledge from DSMs provides a strong foundation for LLMs, promoting more informed and trustworthy language generation, and ultimately catering to the demands of diverse and complex queries from senior students.

Knowledge constraint: In this mode, we enforce additional constraints from DSMs on the LLMs' output to ensure responses that adhere to the defined domain boundaries, while avoiding any unrestricted or irrelevant content. To begin, a specific domain scope, such as mathematics, history, and science, is identified. We then gather domain-specific datasets containing relevant texts and information, which are used to train an external domain-specific language model acting as a discriminator for each domain. LLMs and DSMs are combined within a loop: if DSMs render a negative judgment on LLMs' output, we fuse domain-specific information from DSMs to regularize the output until a satisfactory answer is generated within the knowledge boundary. This iterative process is complemented by the adoption of RLHF, wherein human feedback is used to regularly update and fine-tune the constraints of DSMs and LLMs. The mode strikes an effective balance between creative language generation and adherence to specific domains, thereby paving the way for a more dedicated learning experience.

## 3 Applications

### 3.1 Group learning

Group learning, also referred to as collaborative learning or cooperative learning, is an educational approach where students work together in small groups to achieve shared learning objectives (Wilson et al., 2007). It recognizes that learning is an active and social process with the following key elements:

1. Collaboration: Group learning emphasizes cooperation and collaboration among students. It promotes effective communication, active listening, and collective efforts toward shared goals.

2. Active engagement: Group learning encourages active engagement rather than passive learning. Students actively participate in discussions, debates, and problem-solving activities, facilitating a deeper comprehension of the subject matter.

3. Reflection and feedback: Group learning often involves reflection and feedback mechanisms where students assess their own performance and provide constructive feedback to their peers. This process enhances cognitive skills, self-assessment abilities, and the capacity for continuous improvement.

Considering these fundamental features, the LDMC framework offers a wide range of possibilities for facilitating group collaboration, discussions, and debates in educational settings. Here are some specific ways in which LDMC can contribute:

Maintaining goal alignment: The diverse ideas and perspectives of group members may sometimes steer the team away from its original objectives (Ma et al., 2023). LLMs can provide consistent and effective monitoring, while DSMs are there to ensure that everyone's goals are aligned with the ultimate goal of the team within a controllable topic boundary.

Sustaining communication vitality: Maintaining active communication within the team is crucial for successful task completion (Hickson et al., 2007). In LDMC, DSMs can monitor and identify instances or periods characterized by diminution in the team's energy and intervene promptly to provide motivation, while LLMs are there to intervene in the conversation by asking questions, offering incentives, or providing clues.

Synchronizing learning progress: LDMC can contribute to synchronizing the learning progress and ensuring equal participation among students. By analyzing the interactions and keeping track of the progress of each team member, LDMC helps address each student's concerns and ensures that everyone's problems are resolved at every stage of the

collaboration, thus synchronizing their individual learning journeys.

## 3.2 Individual intelligent tutoring

The creation of individual ITS (Anderson et al., 1985) is one area where LDMC can greatly influence the field of education. These advanced language frameworks possess the ability to understand and generate human-like text, making them well-suited for assisting learners in various subjects. By leveraging their disciplinary knowledge and NLP capabilities, LDMC can tailor educational content to meet the unique needs of each student. No matter it is helping with math problems, explaining complex concepts, or providing interactive exercises, LDMC-powered ITS has the potential to revolutionize the way we teach and learn. With personalized tutoring experiences, students can receive immediate feedback, adapt their learning pace, and explore different learning paths. The integration of LDMC into ITS has the potential to enhance educational outcomes, increase engagement, and empower learners to achieve their full potential. Below are some examples of how LDMC can influence the field of ITS:

Personalized support: By tailoring its suggestions and responses to the choices and goals of each learner, LDMC can provide customized and interactive assistance to self-directed learners. This can be valuable especially for students in remote learning environments.

Resource accessibility: LDMC offers enhanced accessibility for learning resources in various forms. It can be accessed through various platforms, including websites, smartphone apps, and messaging services.

Life-long learning companion: Learning is a life-long journey that requires ongoing motivation and evolving goals. In LDMC, specific components associated with LLMs serve as human-aligned text generators, while other components related to DSMs are dedicated to recording personal development. LDMC can serve as a life-long learning coach, providing encouragement, reminders, and study tips.

Self-assessment and reflection: Learners can leverage LDMC to reflect on their progress and learning, as well as to identify areas where they may require further assistance or direction.

## 3.3 Classroom management

Managing student behavior is an essential aspect of classroom management (Wang YZ, 2021). In addition to providing suggestions on establishing classroom rules, addressing disruptive behavior, and fostering student engagement, LDMC can assist teachers in creating clear and consistent expectations for students. By engaging in a conversation with LDMC, teachers can discuss their classroom dynamics, the age group of their students, and the specific challenges they face. Based on this information, LDMC can offer guidance on developing comprehensive sets of rules and expectations that are appropriate for the class's state and conducive to a positive learning environment (Ye et al., 2022). These rules can cover areas such as respect, collaboration, active participation, and responsible technology use.

Timely assessment and feedback: Integrating LLMs and DSMs in classroom management can streamline the assessment and feedback process. LLMs can be employed to automate grading and provide adaptive templates for assignments, quizzes, and tests. DSMs can assist in offering subject-specific knowledge and skills, enabling teachers to gain comprehensive insights into each student's academic progress. This efficiency in assessment and feedback not only saves time for teachers but also facilitates offering timely and constructive feedback to students, promoting continuous improvement in their learning outcomes.

Efficient lesson planning: LDMC would significantly enhance the process of lesson planning for teachers. LLMs, with their natural language generation capabilities, can assist teachers in generating comprehensive and coherent lesson templates, and incorporating relevant content and learning objectives. DSMs, with access to domain-specific knowledge and resources, can supplement the lesson plans with subject-specific materials, references, and interactive activities. This collaboration streamlines the lesson preparation process, enabling teachers to create well-structured and resourceful lessons that cater to the specific needs and interests of their students.

## 3.4 User study

To evaluate the effectiveness of LDMC in group learning scenarios, we conducted a user study with a small-scale group of 30 students. These

scenarios materialized through collaborative programming tasks. In this study, vanilla LLM, LDMC w/o LSM, and full LDMC assumed the role of the instructor, collaborator, or exciter within the group, offering consultation, cooperation, and encouragement services. After the completion of a group task, we gathered feedback (satisfaction score) from the students regarding the accuracy, relevance, and positivity of their responses. Namely, the score would be 1 if the student is satisfied with the role played by the model, and 0 otherwise. The results are reported in Table 1. These findings suggest that LDMC demonstrates promising results in enhancing group learning experiences.

**Table 1  User study in a group learning scenario**

| Model | Satisfaction score | | | Total score |
|---|---|---|---|---|
| | Instructor | Collaborator | Exciter | |
| LLM | 22 | 23 | 14 | 59 |
| LDMC w/o LSM | 21 | 24 | 17 | 62 |
| Full LDMC | 25 | 26 | 21 | 72 |

w/o: without

## 4  Conclusions

This paper introduces an LDMC framework for smart education along with application examples and case studies. LDMC is a new model collaboration paradigm that learns from different abstraction levels, different sources, and different perspectives. These models are deeply entangled with, and reinforced by, each other, and such collaboration yields MKRs, fostering personalized and adaptive educational experiences. We explore various applications of the LDMC framework in the context of smart education. Through the method of conducting a user study in the context of group learning, we could ascertain that LDMC represents an advanced and comprehensive educational assistance framework that is enriched with intelligent capabilities and thus adept at handling various educational roles. With the continuous advancement of AI, this framework is poised to offer promising potential in significantly impacting the field of smart education.

## Contributors

Yawei LUO designed the research, conducted the experiment, and drafted the paper. Yi YANG revised and finalized the paper.

## Conflict of interest

Yi YANG is an editorial board member of *Frontiers of Information Technology & Electronic Engineering*, and he was not involved with the peer review process of this paper. Both authors declare that they have no conflict of interest.

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