**北京邮电大学 本科毕业设计（论文）中期进度报告**

**Project Mid-term Progress Report**

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| **学院**  **School** | International School | **专业**  **Programme** | **e-Commerce Engineering with Law** | | |
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| **论文题目**  **Project Title** | AI-Enhanced Student Skills Development Tracker | | | | |
| **是否完成任务书中所定的中期目标？Targets met (as set in the Specification)?**  NO –The section on fine-tuning models using datasets is not complete.  Reason –There is some misunderstanding about the project in the proposal stage. At current stage of the mission, it is more important to build a reasonably system than to train fine-tuning models. The NLP required at this stage can be used directly by native models and API. Data set training models will begin as soon as the basic build of the system is complete. | | | | | |
| **已完成工作 Finished work:**   1. **Theoretical Justification for Collaboration Tracking**   At the early stage of the project, after many discussions with the tutor, we made clear the design direction of taking collaboration ability as the core evaluation index. The selection was based on the following consensus:  **1.1 Practical Limitations of Traditional Assessment**  Traditional assessment systems have long faced a fundamental contradiction in group work practices: an excessive focus on final deliverables (e.g., project reports, functional prototypes, or presentation performance) while neglecting the value extraction and skill development inherent in collaborative processes. This assessment paradigm essentially simplifies the complexity of team dynamics, and its limitations are increasingly evident in real-world educational contexts. Taking a typical software development team as an example, instructors often grade students based on explicit metrics like code functionality or interface aesthetics, yet struggle to capture critical process-oriented elements such as collaborative interactions among members. Research indicates that traditional grading systems, due to their overemphasis on observable outputs (e.g., verbal participation), lead to two core issues:  First, the "silent contributor" value gap (Hmelo-Silver et al., 2013). These students may advance team progress through non-verbal means, such as continuously refining documentation structures, coordinating resource allocation during critical phases, or building knowledge-sharing frameworks. Their contributions act as the "lubricant" in a mechanical system—though not directly generating visible outputs, they determine overall efficiency. Yet their work is often relegated to a "black box" (Interactional Research Into Problem-Based Learning, 2022).  Second, the absence of process-oriented competency evaluation. Skills highly valued by modern employers, such as team leadership and cross-cultural communication, are inherently cultivated through dynamic interactions like conflict resolution and role adaptation. Traditional assessments, however, reduce these competencies to static descriptors on resumes.  **1.2 Technical Feasibility of Multimodal Data Integration**  The limitations of traditional assessment stem from a disconnect between educational measurement tools and the complexity of collaborative behaviors. Shifting focus to digital collaboration environments reveals that multimodal data offers a technological pathway to address this challenge. Modern teamwork platforms (e.g., GitHub, Tencent Meeting) inherently generate structured and semi-structured behavioral traces: version control systems meticulously document the spatiotemporal distribution of code contributions, collaborative editing preserves the incremental process of knowledge co-construction, and instant messaging tools archive decision-making dialogues. Through multidimensional AI-driven analysis, such data can be transformed into new metrics for assessing collaboration quality—technically, natural language processing (NLP) tools can extract knowledge co-construction features from interaction logs (Wang Yiyan & Zheng Yonghe, 2022; Wilson Chango, 2023).  Correlational analysis of these heterogeneous datasets can uncover implicit collaboration patterns. For instance, a member who contributes minimally during requirement discussions might drive project progress indirectly by influencing others’ commit behaviors through sustained code refinements. Such cross-modal contribution recognition mechanisms enable the development of a more holistic competency evaluation framework.   1. **Core elements of effective collaboration**   In collaborative learning scenarios, the characteristics of effective collaborators can be systematically defined and evaluated by multidimensional indicators. Based on literature analysis, the following three dimensions are discussed, and the measurement path is illustrated in combination with specific quantitative methods.  **(1) Engagement**  **Definition:** The ability of collaborators to drive the achievement of team goals through substantial contributions (e.g., task division, idea generation).  **Key Indicator:** Task contribution rate  **Data Sources:** Version control systems (Git), task progress reports, member file upload records, task assignment tables, teacher grading sheets  **Measurement:** Proportion and diversity of individual workload in collaborative tasks (e.g., code submissions, document writing, data analysis, etc.)  **(2) Communication Efficacy**  **Definition:** The clarity and bidirectionality of information transfer.  **Key Indicator:** Information entropy value  **Data Sources:** Group discussion records (e.g., WeChat chat logs)  **Measurement:** Analysis using natural language processing (NLP), outputting positive/neutral/negative scores  **(3) Accountability**  **Definition:** The fulfillment of team commitments and respect for others' contributions, providing specific, actionable, and emotionally positive peer feedback.  **Key Indicator:** Specificity of feedback  **Data Sources:** Group discussion records (e.g., WeChat chat logs), peer evaluation sheets  **Measurement:** Use natural language processing (NLP) to analyze whether the feedback contains specific examples or step-by-step suggestions, outputting positive/neutral/negative scores.   1. **Recommendation Engine Design**   Based on the above indicators, the system design can be modular corresponding to ensure the "indicators - data - function" closed loop:  **(1) Data Collection**  The first step in the system is to collect data input. The system collects data through submitted jobs or other forms of data (such as text, job results, etc.), and the data collection module is responsible for integrating these inputs into the system after simple processing, and passing them to the subsequent data processing stage.  **(2) AI Analysis & Skill Map Generation**  The cleaned data is fed into an AI Analysis Engine, which uses algorithms to score students on different dimensions of collaboration.  **(3) Feedback generation and Smart Feedback System**  The system will generate personalized feedback based on the analysis results. This feedback can include specific suggestions for improvement, recommendations for learning resources, and more. The system distributes feedback to different user interfaces  **(4) Data Storage**  All data and feedback are stored in a database  **New Cycle & Feedback**  Once feedback is generated and distributed, the system enters a new evaluation cycle. New data and feedback will further refine the students' skill map, forming a closed loop of continuous improvement. This enables the recommendation system to track the development of students' skills.    Figure 1 Architecture Diagram   1. **Prototype Design**   Based on a collaborative capability assessment framework determined above, a prototype system has been build based on NLP, which can automate the entire process of data acquisition, AI analysis, and feedback generation.  The DeepSeek-R1 has been selected for its superior understanding and cost-efficiency in educational contexts. Its distilled version (DeepSeek-R1-Distill-Qwen-7B) has been deployed on Alibaba Cloud. Future work includes fine-tuning this model using annotated collaboration data via LoRA to enhance behavior classification accuracy, targeting 90%+ precision for critical metrics like conflict resolution detection.  In the current phase of the project, the main goal is to design a functional prototype that can be used to achieve a simple collaboration capability assessment based on student participation in academic activities. The system is able to score from 0 to 5 on different dimensions based on pre-designed input text data and provide insights and feedback.    Figure Simulation Demo show  The system code has been put on GitHub repository:  <https://github.com/bnd1970/Final-Year-Project-AI-Enhanced-Student-Skills-Development-Tracker>  **References**  [1] Hmelo-Silver, C. E., Chinn, C. A., Chan, C., & O'Donnell, A. M. (2013). The International Handbook of Collaborative Learning. Routledge.  [2] Wang, Y. Y., & Zheng, Y. H. (2022). Duo modal xuexi fenxi de jishu lujing yu jiaoyu yingyong [Technological pathways and educational applications of multimodal learning analysis]. *China Educational Technology, 41*(3), 45–53. | | | | | |
| **尚需完成的任务 Work to do:**   1. **Core task:** Complete a fully functional circular recommendation system 2. **Ability Map:** Correlate collaborative ability data with academic achievement to build a visual growth path for students. 3. **Adaptive recommendation engine:** track and record students' growth, and automatically push resources according to weaknesses (such as weak conflict resolution ability → recommend to strengthen learning in this field). | | | | | |
| **存在问题 Problems:**   1. **Functional limitations of the system:** the current system only realizes the feedback ability for the text quality of group assignments, and the current system has not realized long-term tracking 2. **Data diversity Limitation:** The existing system features only cover text document reading and writing 3. **Lack of user interaction:** The current system has not implemented user-friendly data visualization 4. **Hardware limitations:** System response time is slow | | | | | |
| **拟采取的办法 Solutions:**   1. **Function expansion:** multi-modal data access to achieve comprehensive analysis of different types of data in group work; Design historical track database to realize long-term tracking 2. **Report readability optimization:** Design a feedback template engine to provide visual analysis results and reports 3. **Cloud migration:** Deploy the system to the cloud | | | | | |
| **论文结构 Structure of the final report: (Chapter headings and section sub headings)**  *Abstract****2***  Keywords**2**  Chapter 1: Introduction**3**  1.1 Project Motivation3  1.2 Objectives3  Chapter 2: Background**4**  2.1 Collaboration Metrics in Education5  2.2 LLMs in Skill Assessment5  Chapter 3: Design and Implementation**4**  3.1 System Architecture5  3.2 Model Training Workflow 5  3.3 Frontend-Backend Integration 5  Chapter 4: Results and Discussion**4**  4.1 Simulation Outcomes5  4.2 Model Accuracy Analysis5  4.3 User Feedback Summary5  Chapter 5: Conclusion and Further Work**4**  5.1 Key Contributions 5  5.2 Limitations5  5.3 Future Directions5  References **4**  Acknowledgement **4**  Appendices**4** | | | | | |