# Riding on the Back of a Whale: A Hackathon Framework for Introducing High School Students to Large Language Models

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**Abstract.** As large language models (LLMs) become more integrated into daily life, it is crucial to foster AI literacy among high school students. However, most AI courses target college-level learners and assume prior knowledge, while high schools often lack the foundational curriculum and infrastructure for traditional LLM education. To bridge this gap, we present a hackathon-based framework that makes LLM learning accessible, engaging, and hands-on. The program combines interactive lectures on core LLM concepts with a guided competition where students fine-tune models and build real-world applications, such as healthcare chatbots. This approach boosts motivation, programming skills, and practical understanding. Post-hackathon survey results show students gained both functional LLM experience and foundational knowledge. Furthermore, our framework can be extended to broader audiences, including learners without prior AI/NLP experience, offering a rapid, application-driven introduction to LLMs.

**Keywords:** AI Literacy · Hackathon-Based Learning · Large Language Models Education

## 1 Introduction

Education has long been a cornerstone of society, with AI education becoming increasingly vital in recent years. AI literacy is recognized as a crucial skill


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for students in the $21^{st}$ century [14,18,19]. As AI technologies rise in prominence, integrating AI education into K-12 schools—particularly high schools—has gained momentum to prepare students for an AI-driven future [4,10,19,23]. Students should not only understand AI concepts but also gain practical skills for solving problems and designing solutions [17,18,25]. With the rise of LLMs, we aim to provide high school students aspiring to enter tech fields with foundational knowledge and skills in LLMs. Traditionally, LLM curricula are designed for university-level students and require strong math and computer science backgrounds, making them less accessible to younger learners. While AI education is being integrated into K-12 curricula, studies on LLM-specific education are limited [20,27,28]. Furthermore, these curricula often lack customization for high school students. Modern teaching methods like collaborative, project-based, and game-based learning enhance engagement and social skills [17]. Recent hackathons and competitions combine these methods but often provide only basic exposure to generative AI, especially LLMs. To improve LLM education for high school students, we propose a structured hackathon with interactive lectures and guided competition, reinforcing learning through hands-on application.

Our contributions include: (i) We develop comprehensive educational resources, including lecture slides and instructional videos, to teach foundational LLM concepts, fine-tuning techniques, and required knowledge to deal with LLM limitations; (ii) We design detailed, step-by-step, hands-on tutorials with accompanying code, enabling students to build a functional LLM application; and (iii) We propose a structured hackathon model specifically designed to engage high school students in LLM applications, fostering both AI literacy and hands-on problem-solving skills.

## 2 Related Works

*Pedagogical Approaches for Teaching Artificial Intelligence in High School.* Effective AI education often uses practical approaches such as collaborative, project-based, and game-based learning [17]. Collaborative learning builds teamwork and critical thinking through group problem-solving [3,13,14]. Project-based learning emphasizes solving real-world problems via structured projects [7–9,16]. Game-based learning boosts motivation and understanding through gameplay and gamification [6,12,15,22,26]. Recent AI education efforts have merged pedagogical strategies into hackathons, where students build AI solutions in teams and compete for prizes. For instance, [1] used Scratch to teach explainable AI, while [21] offered a month-long ML and NLP course with projects. However, LLM-focused instruction in high schools remains limited due to infrastructure challenges and the difficulty of simplifying complex concepts, requiring both pedagogical and technical expertise.

*Large Language Model Competitions for High School Students.* AI competitions enhance high school education by linking theory to real-world practice [2]. Online ones like Microsoft's Imagine Cup Junior and ColorShapeLinks [5] increase engagement. While many programs promote AI literacy, few focus on LLMs. WAICY includes an LLM track but centers on prompt engineering without structured learning or mentorship. In contrast, our competition provides guided mentorship, in-depth courses on prompting, optimization, and AI ethics, plus curated materials to ensure both theoretical and practical understanding of LLMs.

# 3 Large Language Model Hackathon Framework

## 3.1 Learning Outcomes

Our competition serves as an educational means, providing participants with specific learning outcomes. By the end of the competition, students will achieve the following *Learning Outcomes* (LO): (*LO1*) Understand fundamental LLM concepts; (*LO2*) Be able to implement an LLM-powered chatbot; (*LO3*) Well collaborate in a diverse inter-school team; and (*LO4*) Develop awareness of practical LLM applications. Notably, *LO4* is intended to inspire students to pursue further learning in LLMs and AI, fostering their interest in higher education.

## 3.2 Material Description

Our program introduces LLM fundamentals through a structured curriculum of lectures, activities, and a hackathon. We developed necessary materials for teaching LLMs tailored to high school students, including lecture slides, instructional videos, and a hands-on guide for the hackathon, with sample code and interactive notebooks. These resources enable students to immediately experiment with LLMs and increase engagement. All these materials are available at OSF Link. Topics were selected based on the intended learning outcomes, covering LLM basics in *L01*, Retrieval-Augmented Generation (RAG) techniques [11] in *L02*, and LLM training and fine-tuning for domain-specific applications in *L04*. Preparation of the materials began six weeks prior to the hackathon. One week before the event, we conducted rehearsals among team members, including first- to fourth-year undergraduates and Computer Science (CS) professors. Based on these rehearsals, we adjusted the content to fit within the time constraints and removed advanced concepts that required a strong CS background and did not align with the learning objectives.

## 3.3 Preparation for the Hackathon

*Mentor Team.* We recruit senior undergraduates as mentors based on team numbers. Each team gets a dedicated mentor selected for strong academics and LLM experience. Mentors must have an $A$ in a Machine Learning course and at least three months of LLM experience via projects or thesis work. Selection is based on a composite score (Eq. 1).

$$score = 0.6 \times course\_score + 0.4 \times \left(\frac{5}{3}\right) \times months \tag{1}$$

In (1), the *course_score* is scaled to a 10-point scale with the following standards: $A^+ = 10$, $A = 9$, $A^- = 8$, $B^+ = 7.5$, $B = 7$, $B^- = 6.5$; and *months* represents the number of months the mentors have experience with LLMs.

*Invited Speakers.* We invited four distinguished experts, including academic scholars and industry practitioners, to deliver presentations on LLM topics. These presentations are structured into four lectures, addressing the following key areas: an overview of LLMs, RAG, recent advancements and emerging techniques in LLM research, and a hands-on tutorial focused on the fine-tuning and deployment of LLMs.

*Awards and Prizes.* Awards have been established to recognize the top-performing teams in the competition. These awards comprise four distinct categories: First Prize, Second Prize, Third Prize, and two Honorable Mentions. The monetary value or nature of these awards is subject to the allocated organizing budget and may vary based on the geographical location or the scale of the hackathon.

*Access to LLM APIs.* For the competition, participants are granted access to two LLM APIs to facilitate experimentation, dataset creation, and comparative analysis against their own LLM implementations. The first API provided is GPT-4o, hosted on the Azure platform, with each team allocated a budget of $50 for API usage. The second API is our in-house developed LLM, which is made available to students without usage restrictions. To ensure efficient API management, LiteLLM is employed as a proxy system to handle API calls.

### 3.4 Executive Plan

We propose a two-day hackathon with a structured learning experience through lectures, teamwork, and hands-on application. On the first day, activities begin with two lectures on introducing LLM fundamentals and RAG. After the lunch break, the students come to interactive lectures, in which they gains practical knowledges about how LLM works and how to finetune an LLM. The day concludes with the official launch of the hackathon, during which students form teams of 4âĂŞ6 to tackle real-world challenges. The second day starts with a project pitching session where student teams present their ideas, receive feedback, and refine their solutions. In the afternoon, final presentations are evaluated by a panel based on technical execution, creativity, and impact (scoring rubric). Awards are given for outstanding projects, and the event concludes with a gala dinner.

## 4 Results

### 4.1 Learning Material Evaluation

In this section, we compare the effectiveness of our teaching materials with other well-known AI educational resources. Since the criteria for evaluating AI teaching

**Table 1.** Evaluation of Teaching Materials

| Course | Easy Adaptation | Localization | Examples & Exercises | Clarity & Coverage | Age-Suitability |
|---|---|---|---|---|---|
| Generative AI with Large Language Models | 3 | 5 | 4 | 4 | 2 |
| Generative AI Engineering with LLMs Specialization | 3 | 5 | 5 | 5 | 2 |
| Our materials | 5 | 5 | 5 | 4 | 4 |

**Table 2.** Comparison of our competition with the others

| Competition | Content | Time | Mentors | Place |
|---|---|---|---|---|
| ISEF | STEM | Over months | Professionals | Hybrid |
| IOAI | AI | Several days | AI Experts | In-person |
| WAICY | AI | Several days | – | Hybrid |
| BLAST AI | AI | 8 weeks | Volunteers | Hybrid |
| HackNYU | Beyond STEM | 48 h | Professionals | In-person |
| Hack the North | STEM | 36 h | Volunteers | In-person |
| MHacks | Beyond STEM | 36 h | Volunteers | In-person |
| NASA Space Apps | STEM | 48 h | Professionals | In-person |
| PennApps | Engineering | 48 h | Professionals & Graduate students | In-person |
| Ours | LLMs only | 36 h | Well-selected undergraduates | Hybrid |

materials are not extensively studied, we draw on the framework proposed by [24] to establish our own set of evaluation criteria.

We selected two online courses on Coursera for comparison, including *Generative AI with Large Language Models*, and *Generative AI Engineering with LLMs Specialization*. The selected courses originate from well-known organizations (IBM, AWS, and DeepLearning.AI), have more than 4.5 stars, target people without a strong engineering background, and have been studied more than 5,000 times. Our evaluation of these courses is presented in Table 1. In summary, our teaching materials are designed to be clear and accessible for high school students, incorporating a variety of examples and exercises to enhance understanding. However, a slight limitation lies in the coverage of LLM topics, as the materials were designed for hackathon-based teaching. This approach prioritizes quick knowledge acquisition without overwhelming students, resulting in a focused and less comprehensive coverage.

### 4.2 Competition Analysis

We compare our competition with three leading high school competitions, ISEF, IOAI, and WAICY, and six well-established high school hackathons: BLAST AI, HackNYU, Hack the North, MHacks, NASA Space Apps, and PennApps. The comparison focuses on key criteria related to content and organizational structure. Table 2 highlights the distinguishing features of our hackathon. Unlike ISEF, IOAI, and NASA Space Apps, which cover a broad range of STEM and AI topics, our hackathon is uniquely dedicated to LLMs, offering a specialized and in-depth exploration of this emerging field. Structurally, it aligns with established competitions and hackathons by adopting a 36-hour format, hybrid participation model, and mentorship framework. Similar to HackNYU and PennApps, our hackathon provides expert guidance, though with a targeted focus on LLMs. This specialization, combined with a hybrid structure and structured mentorship, establishes our competition as a novel and impactful platform for engaging with LLM-related challenges.

### 4.3 Implementation Results

We implemented the hackathon as 2024 CSE Summer School at University of Technology - VNU-HCM, selecting 50 students from 108 registrants, while ensuring diversity in gender, grade, and schools. Six months after the hackathon, we conducted a survey and received 36 responses from the participating students, yielding a response rate of 72%. The anonymized student list, submissions, survey questions, and results are available at OSF Link. We summarize the survey results in Table 3. The cohort consisted of 76% male, 24% female, with 72% in Grade 12, 24% in Grade 11, and 4% in Grade 10, from 29 schools. Students were assigned to 10 groups, each with a mentor.The follow-up survey after six months showed a gap between theoretical knowledge (50% intermediate understanding) and confidence (25% able to explain LLM principles). Fine-tuning and prompt engineering were well understood (72.2%), while bias and ethics were less familiar (22.2%). Most students (83.4%) implemented a chatbot but faced challenges with response accuracy (75%), with 83.3% believing prompt modifications could help. Time management (50%) and communication barriers (27.8%) were the biggest difficulties. Despite this, 77.7% had positive teamwork experiences. After the hackathon, 72.2% reported high awareness of LLM applications, and 88.8% expressed interest in further LLM study, highlighting the event's success.

**Table 3.** Survery results

| Questions | Summarized Results |
|---|---|
| Q1: What is your current level of familiarity with Large Language Models (LLMs)? | 5.6% no knowledge; 41.7% basic knowledge; 50.0% intermediate knowledge; 2.8% advanced knowledge |
| Q2: How confident are you in explaining the basic working principles of LLMs? | 5.6% not confident; 25% somewhat confident; 44.4% neutral; 19.4% confident; 5.6% very confident |
| Q3: Which key concepts related to LLMs do you feel most comfortable with? (multiple answers) | 55.5% tokenization; 66.6% training and inference; 72.2% fine-tuning and prompt engineering; 22.2% bias and ethical considerations |

continued

**Table 3.** continued

| Questions | Summarized Results |
|---|---|
| Q4: How well do you understand the strengths and limitations of LLMs? | 5.6% poorly; 22.2% somewhat well; 63.9% moderate well; 8.3% very well |
| Q5: Have you successfully implemented a basic chatbot using an LLM? | 5.6% Yes, independently; 77.8% Yes, with helps from peers/mentors; 8.3% No, but I understand the process; 8.3% No, and I need further clarification |
| Q6: Which aspects of chatbot implementation did you find most challenging? (multiple answers) | 41.7% handling user inputs effectively; 75% improving response accuracy; 41.7% managing biases and ethical concerns; 41.7% understanding API integration |
| Q7: How comfortable are you with modifying prompts to improve chatbot responses? | 5.6% not comfortable; 2.8% somewhat comfortable; 8.3% neutral; 69.4% comfortable; 13.9% very comfortable |
| Q8: How would you rate your experience working in a team on this project? | 0% very negative; 2.8% somewhat negative; 19.4% neutral; 44.4% somewhat positive; 33.3% very positive |
| Q9: What challenges did you encounter while collaborating with your team? (multiple answers) | 27.8% communication issues; 27.8% technical disagreements; 19.4% task delegation difficulties; 50.0% time management problems; 2.8% other |
| Q10: How well did your team manage to distribute workload and responsibilities? | 0% Poorly; 27.8% somewhat well; 41.7% moderately well; 30.6% very well |
| Q11: After completing this project, how would you rate your awareness of real-world applications of LLMs? | 2.8% very low; 5.6% somewhat low; 19.4% neutral; 38.9% somewhat high; 33.3% very high |
| Q12: How interested are you in further exploring or applying LLMs in your studies/career? | 0% not interested; 0% slightly interested; 11.1% neutral; 44.4% interested; 44.4% very interested |

## 5 Conclusion

In this work, we present a hackathon framework designed to introduce high school students to the fundamentals of LLMs and provide hands-on experience in developing and applying LLMs to real-world problems. Through lectures and a competition, students gain essential knowledge of LLM design, techniques, and applications, fostering creative problem-solving and bridging theoretical understanding with practical implementation. The program encourages active engagement, deepens comprehension, and helps students explore future career directions in the field. We believe this hackathon equips learners with the fundamental skills and knowledge necessary to effectively use and manage LLMs in their future studies and careers, akin to the ability to "*ride the whale*" of this transformative technology.

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