Token-Level Abstraction in Large Language Models: A Design-Based Inquiry into AI Comprehension Pathways

Michael Ritchot

A Capstone Presented to the Teachers College Faculty

of Western Governors University

20 June 2025

Abstract

This design-based research study explored how high school students experience and learn the concept of tokenization in large language models (LLMs) through a Google Classroom-hosted e-learning module. The research addressed two questions: (1) How do high school students experience scaffolded design elements (e.g., visualizations, analogies, and discussion prompts) in a module teaching tokenization? and (2) What changes in learners' understanding of tokenization can be observed after completing the module? The instruments included pre- and post-assessments, reflection-based surveys, discussion posts, and a scenario-based summative task. Participants consisted of ten students in Grades 9–11 who completed the asynchronous module over three weeks. Stakeholders included students, parents, school administrators, and the researcher-instructor. A mixed methods approach was employed, utilizing descriptive statistics for quantitative data and thematic analysis for qualitative responses. Results demonstrated significant gains in conceptual understanding, with average assessment scores increasing from 3.1 to 4.5 out of 5. Students reported that visuals, analogies, and interactive elements enhanced their understanding and engagement. The findings support the use of scaffolded, multimodal instructional design to teach complex AI concepts at the secondary level and provide design principles that may inform future AI literacy curriculum development.

Table of Contents

Chapter 1: Introduction

Instructional Problem

Learners in Grades 9–11 lack foundational understanding of how AI models process text through tokenization, limiting their ability to critically engage with AI tools. Instruction is needed to bridge this knowledge and skills gap through accessible, scaffolded learning experiences that demystify tokenization and promote responsible AI literacy.

Research Topic

This study investigates how upper secondary students (Grades 9–11) experience the design features of an online module that teaches the concept of tokenization in large language models (LLMs), with a focus on engagement and comprehension. Specifically, it explores how interactive elements such as guided visualizations, analogies, and structured peer discussions support student understanding of tokenization.

This research topic is important because understanding how students experience foundational AI concepts is essential for fostering digital literacy and responsible AI use. By investigating learner experience and learning outcomes within the context of a high school e-learning module, this study can help educators design more effective instructional approaches to teaching complex technical concepts. The findings could inform best practices in AI education, curriculum development, and digital pedagogy for emerging technologies.

Research Questions

1. Learner Experience Focused Question:
    a. How do high school students in an online learning environment experience scaffolded design elements (e.g., visualizations, analogies, and discussion prompts) in a module teaching tokenization in large language models?

2. Learning Outcome Focused Question:
    a. What changes in learners' understanding of tokenization can be observed after completing an e-learning module designed to introduce tokenization in large language models?

Research Purpose

The purpose of this research is to explore how high school learners experience and learn from an e-learning module designed to teach tokenization as a foundational concept in AI. The goal is to evaluate both the instructional design's impact on learner engagement and the effectiveness of the module in improving learners' conceptual understanding. Findings will inform future design decisions for teaching complex computing concepts in age-appropriate and engaging ways.

Chapter 2: Literature Review

Introduction

Educators and researchers increasingly recognize that artificial intelligence (AI) literacy – a basic understanding of how AI systems work – is becoming essential for today's students (Casal-Otero et al., 2023). High school students regularly interact with AI (from search algorithms to chatbots) yet often do so as passive users without understanding the underlying processes. This lack of foundational knowledge, particularly about how AI models process language, can lead to misconceptions or unwarranted trust in AI outputs (Casal-Otero et al., 2023). In response, there is growing interest in teaching secondary students about core AI concepts to foster more critical engagement with AI tools (Casal-Otero et al., 2023). The present review synthesizes relevant literature in three thematic areas that inform our capstone research purpose: (1) Foundational AI and tokenization literacy for secondary students, (2) Instructional design strategies for complex computing concepts, and (3) Engagement and comprehension in online learning environments for high school learners. These themes provide a structured understanding of prior work on AI education content, how best to teach such technical content, and how to ensure learners remain engaged and learn effectively in an online module. In the sections that follow, we discuss each theme in turn, highlighting key findings and patterns across studies and noting their implications for the design of an online tokenization learning module and our focus on learner experience and outcomes.

AI Literacy and Tokenization in Secondary Education

AI Literacy in K-12: There is broad consensus that K-12 curricula should integrate AI topics so that students are prepared to "live and act in a world with a significant presence of AI" (Casal-Otero et al., 2023). AI literacy has been defined as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool" in various contexts (Jin et al., 2024). This definition, from Long and Magerko (2020), emphasizes both understanding and agency – individuals should not only know what AI is but be able to critically appraise and work with AI. Researchers have further argued that AI education should start early; some even suggest AI competency is becoming as important as reading and writing literacy (Casal-Otero et al., 2023). Kandlhofer and Steinbauer (2016), for example, stress that students need to comprehend the fundamental AI concepts embedded in everyday technologies (Jin et al., 2024). Such foundational AI literacy includes conceptual knowledge (how AI works) in addition to practical and ethical understanding (Casal-Otero et al., 2023) In practice, however, AI education at the secondary level is still emerging. National frameworks like the AI4K12 initiative have proposed "Five Big Ideas in AI" (e.g. perception, representation & reasoning, machine learning, natural interaction, societal impact) as guidelines for K-12 curricula, and highlight the importance of collaboration between developers, teachers, and students in designing AI learning experiences (Casal-Otero et al., 2023). Early implementations of AI in K-12 vary widely – from data-driven projects and interactive visualizations to educational games and robotics activities (Casal-Otero et al., 2023) – but there are currently very few unified methodologies on how to introduce core AI concepts consistently in secondary education (Casal-Otero et al., 2023). Notably, a recent systematic review found "hardly any experiences that assessed whether students understood AI concepts after the learning experience." (Casal-Otero et al., 2023). This points to a gap in the literature: while pilot programs and activities exist, we have limited evidence of what students actually learn or how their understanding changes. Our research responds to this gap by focusing on tokenization, a fundamental AI concept, and examining secondary students' learning outcomes and experiences in detail.

Tokenization as a Foundational Concept: Tokenization refers to the process of breaking text into smaller units (tokens) that a machine learning model can interpret. In the context of large language models (LLMs), tokens are the basic building blocks of language input and output (NYU Steinhardt, 2025). For example, a sentence might be tokenized into words or subword pieces, each represented by a numeric code that the model processes. Teaching students about tokenization provides a window into how AI represents and "reads" text. Students typically are not exposed to this concept in standard curricula; they may use AI chatbots without realizing that the AI doesn't understand whole sentences the way humans do, but rather works on sequences of tokens. Building tokenization literacy thus addresses the "black box" perception of AI by revealing one of its most fundamental inner workings. As part of AI literacy, understanding tokenization can help students grasp why an AI model might output an unexpected word, make a typo-like error, or struggle with an out-of-vocabulary term – all of which stem from how the model chunks and encodes text (Wang et al., 2025). Researchers argue that such transparency is key for critical AI literacy, enabling learners to question and contextualize AI outputs instead of accepting them at face value (Casal-Otero et al., 2023; Jin et al., 2024). Indeed, initiatives in AI education have begun to include simplified explanations of natural language processing. For instance, some high school AI curricula introduce the idea that "computers can only understand numbers and not text" and therefore require a step like tokenization to convert language into numeric form (Wang et al., 2025). By demystifying this process (e.g. demonstrating a byte-pair encoding tokenizer in action), educators aim to deepen students' conceptual understanding of AI language models.

Prior Educational Efforts on AI/Tokenization: A few recent educational interventions illustrate how secondary or novice learners can be taught about AI and tokenization. Dennison et al. (2024) developed Prompty, a web-based AI literacy tool for high school students, designed to move them “from consumers to critical users” of LLMs (Dennison et al., 2024). The Prompty tool scaffolds students’ interactions with a large language model by allowing them to experiment with different prompts and compare the outputs (Dennison et al., 2024). Through guided experimentation, students gain insight into how the AI model responds to linguistic input and begin to infer some underlying mechanisms (for example, they might notice that rephrasing a question changes the outcome, hinting at how the model parses input). Although Prompty focuses on prompt engineering and output analysis, it implicitly touches on tokenization by showing students that wording and phrasing (the tokens provided) affect the AI’s response. Another relevant study, though in a higher education context, demonstrated the teachability of tokenization concepts: Wang et al. (2025) introduced a one-hour Generative AI module in a university engineering class to explain LLM fundamentals. Despite being a short intervention, after the module “students reported a clear understanding of tokenizers and word embeddings” while initially these concepts were opaque to them (Wang et al., 2025). The module used a case study of byte-pair encoding and a live tokenizer demo to concretize the concept (Wang et al., 2025). This result is encouraging – it indicates that even a brief, well-designed instructional module can significantly improve learners’ grasp of tokenization. By extension, it suggests that high school students, with appropriate scaffolding, can similarly learn about tokenization and benefit from this knowledge. Across these efforts, a common thread is the importance of making the abstract idea of tokenization tangible. Whether through interactive tools (Prompty) or live demonstrations, students are more likely to internalize the concept when they can observe or manipulate it directly, rather than only hearing a dry explanation. In summary, the literature on AI literacy for secondary students underscores a strong rationale for our focus on tokenization: it is a fundamental AI concept that students currently lack exposure to, and initial studies hint that targeted instruction on this topic can empower learners to engage more critically and confidently with AI. Our capstone module is grounded in this premise, aiming to contribute evidence on how high school students experience and learn tokenization as part of broader AI literacy.

Instructional Design Strategies for Complex Computing Concepts

Teaching a complex computing concept like tokenization to high school students requires thoughtful instructional design. Such concepts are often abstract and can be challenging for learners to grasp without appropriate pedagogical support (Bernstein et al., 2024). Prior research in computer science education and cognitive science highlights several effective strategies for making complex technical content accessible: scaffolding, use of analogies and metaphors, and visual representations/visualizations are frequently cited approaches. This section synthesizes findings on these strategies and how they can be applied to designing an online learning module on tokenization.

Scaffolding and Cognitive Load Management: Scaffolding refers to the instructional technique of providing structured support to learners as they acquire new skills or knowledge, gradually removing the support as learners become more independent. The concept, rooted in Vygotskian educational theory, has been extensively explored in the context of teaching difficult material. From a cognitive load perspective, scaffolding works by regulating the flow of information so it does not overwhelm the learner's working memory (van Nooijen et al., 2024). In other words, breaking down a complex concept into manageable chunks, providing hints or partial solutions, and sequencing tasks from simple to complex helps novices build understanding without being overloaded (van Nooijen et al., 2024). For example, when teaching tokenization, an instructor might first remind students how computers encode simple text (e.g., ASCII codes for characters), then introduce the idea of splitting sentences into words, and only then move to subword tokenization and its necessity for AI models. This stepwise buildup serves to cue relevant prior knowledge and chunk new information into digestible pieces (van Nooijen et al., 2024). Studies have shown that such guided learning outperforms unguided discovery, especially for novice learners facing intricate concepts (van Nooijen et al., 2024). A practical illustration of scaffolding in our context comes from the Generative AI module by Wang et al. (2025): the instructors interwove brief lectures with interactive exercises and included a worked example to concretely demonstrate tokenization (Wang et al., 2025). Specifically, after introducing the concept, they walked through a live example of how a GPT tokenizer breaks down a sample sentence, before asking students to try it themselves (Wang et al., 2025). This gradual release of responsibility – first modeling the process, then letting students practice – exemplifies scaffolding that can build confidence and understanding. The takeaway for designing our module is clear: incorporate scaffolding elements such as guided examples, hints, and incremental challenges so that learners are supported as they approach the challenging idea of tokenization.

Analogies and Metaphors: Analogical reasoning is a powerful educational tool for abstract concepts. By linking new material to a familiar idea, analogies help students form mental models of something they cannot directly see or easily intuit (Bernstein et al., 2024). In computing education research, analogies have been used to explain everything from recursion (e.g., comparing it to nested Russian dolls) to CPU scheduling (e.g., analogizing to wait lines) (Bernstein et al., 2024). Analogies and metaphors create a bridge between the unfamiliar and the familiar, making the learning experience more engaging and the concept more memorable (Bernstein et al., 2024). For instance, to teach tokenization, one might use the analogy of cutting up sentences like puzzle pieces: just as a puzzle must be broken into pieces that fit a certain way, an AI model breaks text into predefined pieces (tokens) that it knows how to handle. This kind of analogy leverages students' existing understanding of puzzles or Lego blocks to represent how an AI "chunks" language. Research indicates that students not only enjoy analogies but often recall complex concepts better when taught in metaphorical terms, especially if the analogy is personally or culturally relevant to them (Bernstein et al., 2024). One study found that students remembered recursion analogies more easily when the analogies referenced familiar themes or interests (e.g., a favorite story or hobby) (Bernstein et al., 2024). The implication is that selecting a relatable analogy for tokenization (perhaps something with words or language that students encounter daily, like texting abbreviations as an analogy to subword tokens) could enhance engagement and understanding. However, it is also noted that creating effective analogies is challenging, and students may need guidance to fully grasp the parallel being drawn (Bernstein et al., 2024). Instructors should explain where the analogy maps onto the concept and where it breaks down. In our module, we plan to integrate analogies and will ensure to discuss the comparison so that students can connect the analogy back to the technical process.

Visualizations and Interactive Representations: Complex computing processes often involve steps or structures that are invisible to learners. Visual representations – such as diagrams, animations, or interactive simulations – can make these processes visible and hence more understandable (Bernstein et al., 2024). Prior work suggests that "high-quality explanations or visual representations such as visualizations and concept maps" are beneficial when learning difficult "threshold" concepts in computing (Bernstein et al., 2024). Visual aids offload some cognitive processing from the verbal to the visual channel, which can reduce overload and help learners form correct mental models. In teaching tokenization, visualizations might include showing how a sentence is split and encoded step by step. For example, an interactive web diagram could depict a sentence flowing into a tokenizer, which then outputs a sequence of tokens (perhaps represented as jigsaw puzzle pieces or blocks), each with a number. Such a visualization allows students to literally see the transformation from text to tokens. Empirical support for visualization comes from a variety of domains: Sanders and McCartney (2016) found that visual concept maps helped students master tricky programming concepts by explicitly mapping relationships (Bernstein et al., 2024). In AI education specifically, some K-12 programs use interactive data visualizations to let students explore AI algorithms (Chittora & Baynes, 2020; von Wangenheim et al., 2021). These interactive tools engage learners by letting them tweak inputs and observe outputs, reinforcing learning through exploration. Our literature review indicates that combining modalities – verbal explanation, analogical narrative, and visual demonstration – is an especially effective strategy for complex topics. By doing so, educators cater to different learning preferences and repeatedly reinforce the concept through multiple representations. In designing the tokenization module, we will draw on this principle by including diagrams or animations of the tokenization process alongside text explanations, and possibly embedding a live demo or simulation that students can manipulate (e.g., an online tokenizer tool where students input a word or sentence and see the tokens).

Integrating Strategies – Patterns and Findings: The strategies of scaffolding, analogies, and visualizations are often most powerful when used in combination. The literature shows they address complementary aspects of learning: scaffolding targets the sequence and support of learning activities, analogies target the initial conceptual hook and relatability, and visualizations target the concretization of abstract ideas. In practice, successful instructional designs for complex computing concepts frequently weave these elements together. For example, a scaffolded lesson might begin with an analogy to introduce the big idea, use a visualization to delve into the mechanism, and include guided practice with feedback to solidify understanding. Studies on teaching with analogies underscore that without proper scaffolding, students might misapply or misinterpret analogies (Bernstein et al., 2024) – hence the teacher's role in guiding discussion is crucial (a note relevant even if our module is online and self-paced, we can guide via explanatory text and checkpoints). Likewise, while visualizations can illuminate, students benefit from prompts that focus their attention on the important parts of the visualization (a form of scaffolding through "cueing") (van Nooijen et al., 2024). In summary, the design literature suggests a few best practices we will emulate: start simple and build complexity (scaffold the tokenization concept from basic to advanced), use familiar frames of reference (analogy/metaphor) to spark intuition, show rather than tell (visualize the tokenization process), and constantly engage the learner in active sense-making (through questions or interactive tasks rather than passive reading). By synthesizing these techniques, we aim to create an instructional module that makes the complex process of tokenization accessible and meaningful for high school students. This pedagogical approach is directly informed by prior research and is expected to enhance both understanding and retention of the concept, as supported by the patterns observed across the studies reviewed.

Engagement and Comprehension in Online Learning for High School Students

Delivering instruction via an online e-learning module introduces another critical dimension: student engagement with the content and their resulting comprehension. In an online learning environment – especially one that is self-paced or without a live instructor – maintaining learner engagement is both challenging and essential for success. This theme of the literature review examines how high school learners engage with online educational content, what factors influence their engagement and understanding, and what strategies can promote a productive learning experience in a virtual setting. These insights will guide the design of our tokenization module to ensure it is not only instructive but also engaging for our target audience.

Defining Engagement and Its Importance: Student engagement is commonly understood as a multi-faceted construct encompassing behavioral, cognitive, and affective dimensions (Hollister et al., 2025). Behavioral engagement involves students' participation and effort in learning activities (for example, time spent on the module, completing exercises, etc.), cognitive engagement refers to their mental investment in understanding the material (e.g. actively thinking about concepts, self-regulating their learning, achieving comprehension), and affective engagement captures their emotional response (interest, enjoyment, or sense of connection to the learning) (Hollister et al., 2025). All three aspects are interrelated and contribute to learning outcomes. In online learning, these engagement dimensions can be harder to foster – students might be physically alone, easily distracted by other online content, or prone to disengage if the material feels confusing or dull. Research during the COVID-19 remote learning period revealed significant engagement challenges: for instance, more than half of students in one survey reported that it was harder to maintain interest and motivation in online classes compared to in-person (Hollister et al., 2025). Many students missed the face-to-face interaction and community of a classroom, which in online settings can lead to feelings of isolation and disengagement (Hollister et al., 2025). This is especially relevant for high schoolers, who often rely on social interaction and teacher feedback to stay on track. The literature consistently shows that engagement is a strong predictor of learning success – students who are more engaged tend to have higher persistence, satisfaction, and performance in online courses (Hu & Xiao, 2025). In a study of high school online course participation, researchers found that students who logged in regularly and spent more time on tasks each week were far more likely to complete the course and earn a passing grade (Pazzaglia et al., 2016). Specifically, most students who dedicated at least ~1.5–2 hours per week to their online course achieved passing grades, whereas those with sporadic or minimal engagement often struggled (Pazzaglia et al., 2016). These findings underscore that an e-learning module must capture students' attention early and sustain it, or else even the best-designed content might not be fully absorbed.

Factors Influencing Online Engagement for Teens: What helps or hinders high school students' engagement and comprehension in an online environment? Recent reviews have synthesized a range of factors. On the learner side, key factors include motivation, prior digital literacy and experience, self-efficacy, and the ability to conduct self-directed learning (Hu & Xiao, 2025). High school students vary in their intrinsic motivation for an online module – some may be very curious about AI and thus internally driven, while others might need external encouragement. Their familiarity with e-learning tools and comfort with independent learning also play a role; students who have not developed good self-regulation strategies might procrastinate or skim through without understanding. On the environment side, factors include the design of the tasks, the usability of the platform, the presence of interactive elements, and opportunities for interaction or collaboration (Hu & Xiao, 2025). A well-structured, user-friendly module with clear instructions and feedback can significantly boost engagement by reducing frustration and confusion. Moreover, incorporating social elements – even something as simple as a discussion forum or showing students' progress relative to peers – can address the affective and social aspect of engagement, creating a sense of community or competition that motivates learners (Hollister et al., 2025). In a K-12 online setting, instructor support remains important too (Hu & Xiao, 2025). While a fully self-paced module might not have a live teacher, providing virtual support (like Q&A resources, or periodic check-ins by an instructor via email/chat) can help keep students accountable and supported. Essentially, high schoolers often need guidance and encouragement to engage deeply with online content, more so than adult learners who may be used to autonomous learning. Self-determination theory (as referenced by some studies (Chiu, 2021) suggests that to foster engagement, an online module should try to satisfy students' needs for autonomy (e.g., allowing some control or choice in the learning process), competence (e.g., giving feedback that helps them see their progress and feel capable), and relatedness (e.g., knowing that others are learning with them or that an instructor cares about their success).

Strategies for Enhancing Engagement and Comprehension: The literature offers several evidence-based strategies to improve online engagement and learning outcomes for high school students. One fundamental approach is clarity and structure: setting clear learning goals and expectations within the module helps students understand what they should be doing and why (Hu & Xiao, 2025). For example, at the start of our tokenization module we might state, "By the end of this module, you will be able to explain what tokenization is and why it matters in AI." Such goal-setting gives learners a target to strive for and can increase their cognitive engagement (they know what understanding they're aiming to achieve). Breaking the module into short, modular sections (micro-learning units) can also prevent cognitive overload and give students a sense of accomplishment as they complete each part. Another key strategy is to incorporate interactive elements to transform students from passive readers into active participants. This might include quizzes, drag-and-drop exercises, or scenario-based questions. Quick formative assessments embedded in the module serve two purposes: they keep students on their toes (behaviorally engaged) and also reinforce comprehension by prompting learners to recall or apply what they just learned. Immediate feedback on these exercises can further enhance learning by correcting misunderstandings in real time. Research suggests that such interactive checkpoints promote deeper cognitive processing, as students must retrieve and use knowledge, not just glance over it (Eduaide.Ai, 2025; Australian Education Research Organisation, 2023). Additionally, multimedia use (e.g., short videos, infographics, or even gamified elements) tends to increase engagement for younger learners accustomed to digital media. A study on online engagement noted that incorporating varied media and frequent changes in activity can re-capture students' attention and prevent monotony or fatigue (Hollister et al., 2025). However, any multimedia must be purposeful and aligned with learning objectives to avoid becoming a distraction. Regarding the social dimension, even if our module is primarily self-study, we can include prompts for offline discussions or reflections that teachers can use in class, or invite students to share their thoughts in an online forum. Peer interaction, when available, has been shown to foster a "sense of community" which correlates with more sustained engagement and better learning in online settings (Hollister et al., 2025). For example, Martin and Bolliger (2018) found that group activities and discussions in online courses helped prevent student boredom and isolation (Hollister et al., 2025). In a high school context, this could be implemented by encouraging students to compare their interpretations of an AI output or collaboratively debug a tokenization example as an optional group task. Finally, to ensure comprehension, the module should promote cognitive engagement by encouraging students to think deeply about the content. This could mean posing open-ended reflection questions ("Why do you think tokenization might cause an AI model to misunderstand a word it hasn't seen before?") to spur critical thinking. Such questions get students to connect concepts and reflect, which are indicators of higher-order engagement (and align with building critical AI literacy, not just factual recall) (Hu & Xiao, 2025; Jin et al., 2024). In summary, the literature on online learning for high school students suggests that our module will be most effective if it is interactive, well-structured, and supportive. Ensuring engagement is not a trivial add-on; it is intertwined with learning – a student who is engaged will put in the mental effort (cognitive engagement) needed to truly comprehend tokenization, whereas a disengaged student may click through without gaining much. Therefore, in designing the e-learning experience, we will apply these best practices: clear objectives, chunked content with practice exercises, multi-modal instruction, and mechanisms to motivate and involve learners throughout.

Conclusion

In conclusion, this literature review has outlined key insights across three areas that together inform the design and implementation of our capstone project on teaching tokenization to secondary students. First, in the realm of AI literacy for secondary students, we found a strong imperative to educate learners about how AI works at a fundamental level. Prior studies and frameworks emphasize that concepts like tokenization – how AI models break down and represent text – are critical for empowering students as informed, critical users of AI (Jin et al., 2024; Casal-Otero et al., 2023). Yet, this is a nascent area: few K-12 initiatives have explicitly tackled such topics, and even fewer have evaluated student learning outcomes (Casal-Otero et al., 2023). This gap in the literature reinforces the importance of our research focus. By concentrating on tokenization, our study addresses a component of AI literacy that has been largely missing in secondary education and will contribute knowledge about how students understand and make sense of this concept.

Second, regarding instructional design strategies, the literature provides a clear roadmap for teaching complex computing concepts effectively. Approaches that scaffold learning and reduce cognitive overload, that connect new ideas to familiar ones through analogy, and that visualize abstract processes have repeatedly been shown to improve student comprehension and retention (Bernstein et al., 2024; van Nooijen et al., 2024). These strategies will directly shape our instructional module. For example, based on these findings we will incorporate step-by-step guided explorations of the tokenization process, use analogies to introduce the concept in an intuitive way, and include visual diagrams or interactive demos to let students see how tokenization works. By grounding our module design in established pedagogical techniques, we aim to maximize students' learning gains and confidence with the material. The literature also highlights that students often need support (scaffolding) when grappling with challenging content – a reminder for us to build in hints, explanations, and progressive difficulty in the module rather than expecting students to absorb everything unaided.

Third, the review of online learning engagement pinpointed the factors that will influence how students experience our e-learning module. High school learners require an environment that keeps them motivated, focused, and active in their learning (Hollister et al., 2025; Hu & Xiao, 2025). Consequently, we will integrate interactive elements and frequent feedback to sustain behavioral and cognitive engagement. The module will be designed with user-friendly and teen-appropriate language and visuals to spark interest. Recognizing that comprehension in an online format is tied to engagement, we will use strategies such as clear goal-setting, segmenting content into short lessons, and posing reflective questions to promote deeper thinking. Moreover, because our research is specifically concerned with learner experience, these literature insights give us concrete aspects to observe and measure: for instance, we might collect data on how engaging students found each part of the module, how much time they spent on interactive exercises, and their self-reported interest and confidence before and after the module. We will also assess their learning outcomes – in this case, understanding of tokenization – through knowledge checks or interview questions, informed by the educational approaches we used (e.g., if we taught via an analogy, do they recall the analogy and does it aid their explanation of tokenization?).

Overall, the literature converges on the idea that content, pedagogy, and delivery must align with the learners' needs for an intervention to be successful. Foundational AI knowledge needs to be taught in a way that students can grasp and care about; effective teaching of such technical content requires intentional design using research-backed methods; and an online platform must actively engage students to achieve meaningful learning. These conclusions directly inform our capstone project's design and methodology. We will develop the tokenization module by applying the reviewed best practices and then examine students' experiences and learning in light of those practices. In doing so, our research not only is guided by prior scholarship but also aims to extend it – providing empirical evidence on how upper secondary students learn from a tokenization-focused AI lesson and how they describe their experience. This can ultimately contribute to the evolving discourse on AI literacy education and help educators better prepare students for a future in which understanding AI is increasingly vital. The literature review thus sets a strong foundation for the capstone, ensuring that our approach is grounded in proven educational principles and aligned with the overarching goal of enhancing both the learner's knowledge and their engagement in learning about AI.

Chapter 3: Research Methodology

Instructional Problem Overview

High school students in Grades 9–11 regularly interact with generative AI tools like ChatGPT but often do so without a foundational understanding of how these tools process language. A key gap in AI literacy is the concept of tokenization—how AI models segment input text into smaller units that can be interpreted and processed by machine learning algorithms. This abstract, technical concept is unfamiliar to most secondary learners, limiting their ability to critically assess AI outputs and contribute responsibly in digital spaces increasingly shaped by such technologies.

Learner analysis revealed that while students are interested in AI, many experience cognitive overload when faced with technical vocabulary and complex internal processes. Without clear, scaffolded instruction, tokenization remains a "black box," reinforcing surface-level engagement with AI and limiting students' capacity for meaningful analysis. Therefore, instructional solutions must explicitly demystify tokenization using accessible, interactive, and developmentally appropriate strategies that align with students' existing digital literacies and learning preferences.

Potential Solutions

1. Google Classroom Hosted Module on Tokenization (Selected Solution)
    a. How This Solution Addresses the Instructional Problem:
        i. This solution offers a complete asynchronous e-learning module hosted in Google Classroom that introduces tokenization through a structured sequence of scaffolded lessons. It addresses the instructional problem by directly targeting learner misconceptions and cognitive overload through

visuals, analogies, guided practice, and interactive reflection. Learners move from basic concepts to deeper application through multimodal instruction aligned to their technological comfort zone.

b. Learning Technology Tools:
    i. Google Classroom: Central hub for organizing and sequencing learning activities
    ii. Google Docs: Instructional content broken into visual, easy-to-follow lessons
    iii. Google Forms: Embedded formative quizzes and reflection checkpoints
    iv. External tokenizer demos (e.g., TikTokenizer): Interactive simulations to show how text is split into tokens
    v. Google Classroom comment threads: Asynchronous peer discussion
c. Advantage:
    i. Google Classroom is widely used and familiar to the learner group, which lowers the barrier to entry and increases engagement. The structured module format allows for careful pacing and chunked content, directly combating cognitive overload. The integrated Google Suite tools provide immediate feedback, visual clarity, and collaboration opportunities, all of which are critical for building conceptual understanding of tokenization in a self-paced format.
d. Challenge:
    i. Transitioning the previously created Canvas module into Google Classroom requires content reformatting and integration adjustments.

e. Mitigation Steps:
   i. Use the original Canvas module as a blueprint for sequencing, pacing, and scaffolding.
   ii. Adapt materials directly into Google Docs and Forms without redesigning core instructional elements.
   iii. Maintain fidelity to learning goals and interaction design while ensuring smoother implementation for this learner group.

2. Canvas-Based Interactive Module on Tokenization (Previous Solution)
   a. How This Solution Addresses the Instructional Problem:
      i. This alternative solution presents a fully structured e-learning module built in Canvas, the LMS used during the design phase. It walks learners through the concept of tokenization using static readings, animations, embedded tokenizer demos, scaffolded formative assessments, and reflection questions. It addresses the instructional problem by explicitly explaining what tokenization is, showing how it works in LLMs, and allowing learners to apply their knowledge through embedded tasks.
   b. Learning Technology Tools:
      i. Canvas LMS: Hosts all module components in one centralized location
      ii. Canvas Quizzes: Checks for understanding after each segment
      iii. Canvas Discussions: Promotes asynchronous peer-to-peer engagement
      iv. Embedded tokenizer tools: Allow students to see tokenization in real-time
   c. Advantage:

        i. Canvas allows for modular, cohesive e-learning design, integrating instruction, assessments, and interaction. The platform supports instructional alignment and engagement strategies aligned with instructional design best practices.

    d. Challenge:

        i. Some students are less familiar with Canvas, and technical friction may reduce participation or quality of responses.

    e. Mitigation Steps:

        i. Provide an introductory navigation guide for students unfamiliar with Canvas

        ii. Offer optional video walkthroughs and troubleshooting steps

        iii. Gather student feedback to refine user experience during the initial rollout

3. Prompt-Based Exploration Tool

    a. How This Solution Addresses the Instructional Problem:

        i. This exploratory module introduces tokenization through guided experimentation using prompt-response tools (e.g., ChatGPT) alongside direct instruction. Students complete a structured series of guided tasks that require them to manipulate input prompts and observe how different phrasings change AI outputs. This inductive process leads to inference-based understanding of tokenization and allows learners to connect theory to practice.

    b. Learning Technology Tools:

        i. OpenAI Tokenizer: Used to visualize tokenization behavior

ii. Google Docs worksheets: Scaffolded activity sheets to guide inquiry

iii. Google Classroom or Padlet: Facilitates peer sharing of findings and questions

iv. Short instructor videos: Clarify how tokenization underpins the observed AI behavior

c. Advantage:

i. This solution increases student engagement and agency by allowing them to investigate real AI outputs in a controlled way. It introduces tokenization through discovery learning, which can be powerful when paired with structured reflection.

d. Challenge:

i. Tokenization may remain implicit if students are not provided with direct instruction to reinforce observed patterns.

e. Mitigation Steps:

i. Include a follow-up lesson with a formal explanation of tokenization

ii. Provide vocabulary scaffolds and real-world analogies after hands-on tasks

iii. Use quizzes and reflections to assess whether students made correct inferences

Selected Solution and Justification

The Google Classroom–Hosted Tokenization Module was selected as the most effective solution for addressing the instructional problem. It combines the explicit instruction of the Canvas module with the familiarity and usability of Google Classroom, ensuring high levels of engagement and accessibility for learners in Grades 9–11. Unlike the Prompt-Based Exploration module, which relies on inference and may leave misconceptions unresolved, the Google Classroom solution provides a structured, scaffolded path from concept introduction to application and reflection.

This platform shift does not alter the core instructional design but enhances the feasibility of implementation and the quality of learner data collected during the capstone. The use of Google Suite tools ensures alignment with students' digital fluency, while formative assessments and visual demonstrations directly address the challenge of teaching a complex, abstract computing concept.

E-Learning Unit of Instruction Description

Module Title: Understanding LLM Tokenization

Module Description: This self-paced Canvas-based module introduces high school students (Grades 9–11) to the concept of tokenization in large language models (LLMs). Through analogies, visuals, embedded quizzes, and scenario-based tasks, learners will develop foundational knowledge of how text is broken into tokens for machine processing. The module emphasizes critical AI literacy by helping students understand and question the inner workings of tools they already use, such as ChatGPT.

Target Audience: Students in Grades 9–11 enrolled in a blended or online learning environment with varying digital literacy levels. The module assumes no prior knowledge of AI or machine learning concepts.

Learning Goal: Students will understand the role of tokenization in AI language processing and be able to analyze simple examples of how AI systems transform text into tokens.

Learning Objectives: By the end of this module, learners will be able to:

- Define tokenization and explain its purpose in the context of large language models.
- Identify how tokenization transforms input text into discrete tokens.
- Analyze tokenization outputs to understand limitations in AI-generated responses.

Assessments

Formative Assessments:

Quick Check – What Are Tokens? This formative multiple choice activity checks for understanding on the fundamentals of what tokens are in the context of LLMs.

Interactive Vocabulary Match Quiz – Matching terms like “token,” “tokenization,” “byte-pair encoding” to definitions.

Discussion Post – Why Does Tokenization Matter To You? Reflection and discussion post asking students to reflect and reply on why tokenization is important in understanding models input and output.

Summative Assessment:

"Tokenization in Action" Scenario Analysis – Learners analyze a real-world prompt and AI output, identify possible tokenization decisions, and explain their reasoning in a short-answer response.

Anticipated Learner Needs

Learner Need 1: Cognitive support for abstract concepts.

- Many learners may struggle with the technical nature of tokenization without visual or real-world supports.

Learner Need 2: Cognitive overload in asynchronous settings.

- Without cognitive chunking, some students may disengage by being overwhelmed.

Addressing Learner Needs

- To support conceptual understanding, the module includes analogies (e.g., comparing tokenization to breaking words into smaller chunks using emojis), and a tokenizer demo link.
- To scaffold pacing and autonomy, the module takes care to break concepts into smaller cognitive chunks, with appropriate check in points.

Learning Technology Tools

- Canvas – Used to design and deliver the module's instructional flow, embed text and media, and include assessments.
- TikTokenizer (external link) – A free online tokenizer tool that allows learners to input their own text and view how tokens are generated in real time.

Justification

- Canvass enables clear organization and integration of visual, textual, and interactive components—crucial for reducing cognitive load and maintaining learner engagement.
- TikTokenizer provides an authentic tool that concretely demonstrates the abstract process of tokenization, supporting deeper learner comprehension through direct interaction.

Addressing the Instructional Problem

The module was developed to close the gap in foundational AI understanding by making tokenization concrete, accessible, and engaging. It addresses the instructional problem in three key ways:

1. Scaffolded Explanations and Visuals: The module introduces tokenization step-by-step, using visuals and analogies (e.g., emojis) to simplify the concept.
2. Interactive Engagement: Quizzes, drag-and-drop tasks, and short reflection and discussion activities sustain attention and promote active learning in a fully online context.
3. Authentic Application: The summative assessment asks learners to apply their understanding to a real-world AI interaction, building their capacity to critically analyze the output of tools like ChatGPT.

Research Methodology

Method

This study will employ a mixed methods approach, integrating both qualitative and quantitative data collection. The rationale for this choice is the dual focus of the study: (1) to explore how students experience instructional design elements (qualitative), and (2) to measure any changes in conceptual understanding of tokenization (quantitative).

Justification:

The first research question focuses on student experience with design elements like analogies, visuals, and prompts. This requires open-ended, descriptive feedback best captured through qualitative methods (e.g., reflection questions and post-module surveys).

The second research question examines learning gains in tokenization concepts, which necessitates pre- and post-assessments with measurable outcomes (quantitative).

This combination allows for a more comprehensive understanding of the module's effectiveness from both learner and instructional design perspectives.

Participants/Stakeholders

Participants:

The study will include approximately 8–12 students enrolled in Grades 9–11 (ages 14–17), participating in an online or blended learning environment. These students will complete the e-learning module asynchronously.

Participant Selection:

Participants will be selected based on an educational cohort accessible to the researcher (e.g., students in a school). All participants will be invited to participate voluntarily, with proper procedures followed if minors are involved.

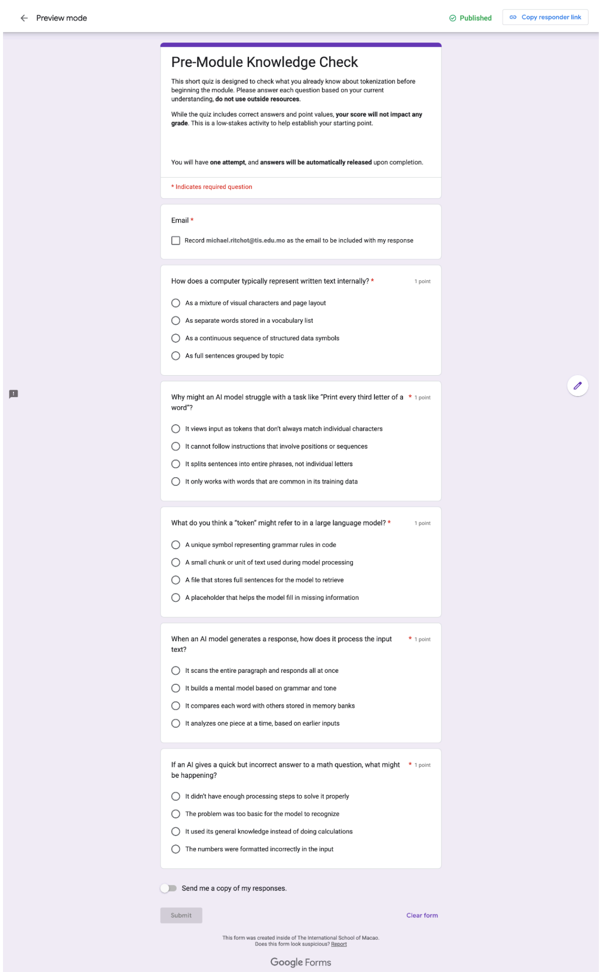
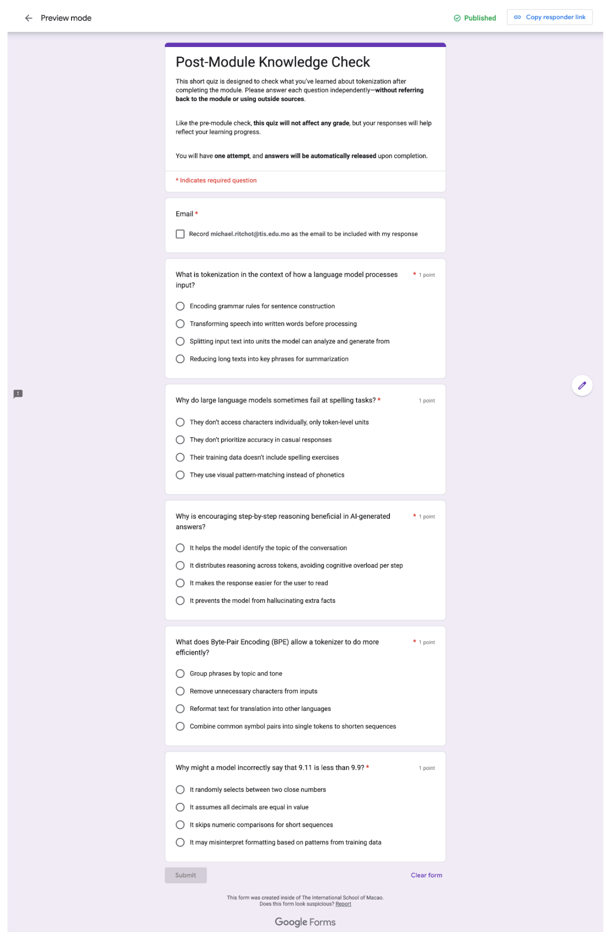
Stakeholders:

- Students: Primary beneficiaries of AI literacy efforts and direct participants in the intervention.
- Parents or guardians: Have a vested interest in how emerging technologies are taught and in ensuring their children become critical, informed users of AI tools.
- Classroom teachers and technology coordinators: Interested in discovering effective strategies for teaching foundational AI literacy.

Data Collection Instrument(s)

1. Pre- and Post-Assessment (Quantitative)
    a. Instrument: A 5 item quiz composed of multiple-choice and short-answer questions assessing conceptual understanding of tokenization.

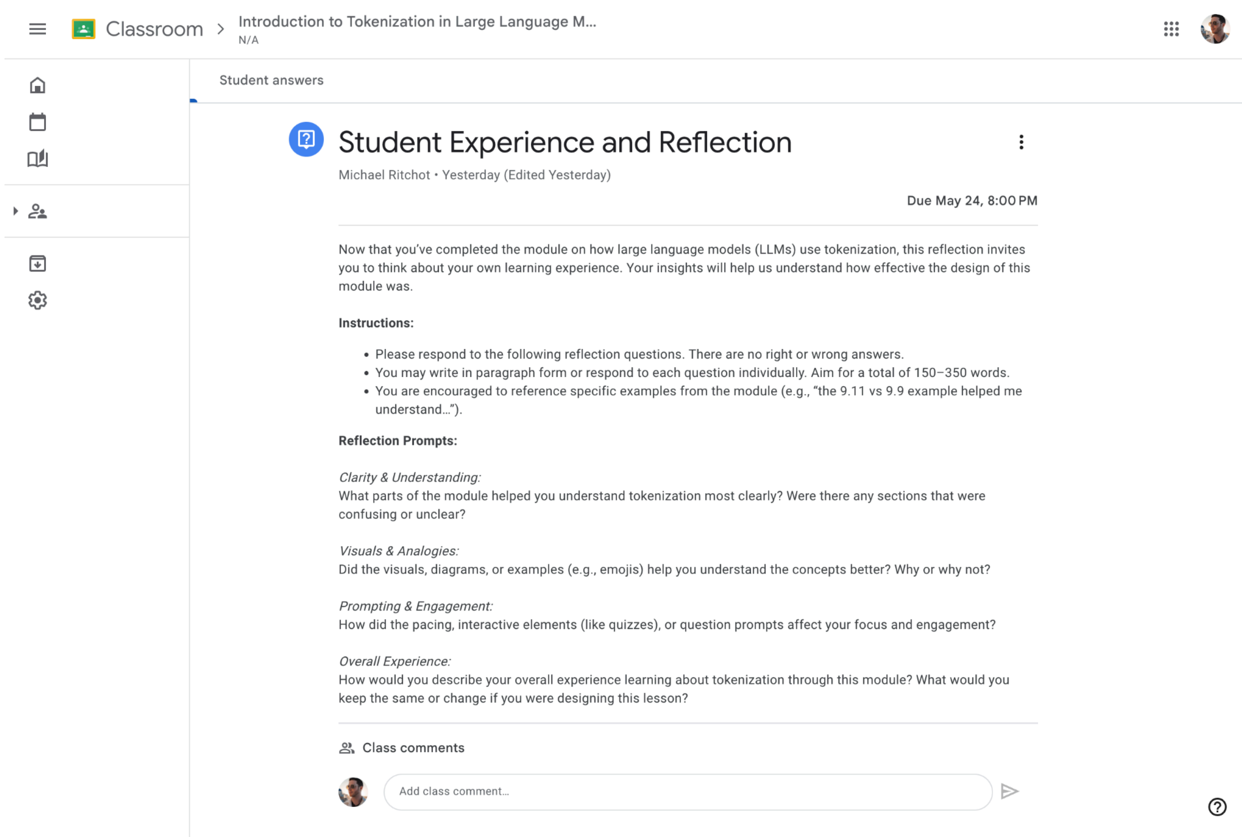
b. Data Provided: Score change from pre- to post-assessment to measure learning outcomes.

<table>
<tr><th>Pre-Module Assessment</th><th>Post-Module Assessment</th></tr>
<tr><td>
Preview mode
Published
Copy responder link
Pre-Module Knowledge Check
This short quiz is designed to check what you already know about tokenization before beginning the module. Please answer each question based on your current understanding, do not use outside resources.
While the quiz includes correct answers and point values, your score will not impact any grade. This is a low-stakes activity to help establish your starting point.
You will have one attempt, and answers will be automatically released upon completion.
* Indicates required question
Email *
Record michael.ritchot@tis.edu.mo as the email to be included with my response
How does a computer typically represent written text internally? * 1 point
As a mixture of visual characters and page layout
As separate words stored in a vocabulary list
As a continuous sequence of structured data symbols
As full sentences grouped by topic
Why might an AI model struggle with a task like “Print every third letter of a word”? * 1 point
It views input as tokens that don’t always match individual characters
It cannot follow instructions that involve positions or sequences
It splits sentences into entire phrases, not individual letters
It only works with words that are common in its training data
What do you think a “token” might refer to in a large language model? * 1 point
A unique symbol representing grammar rules in code
A small chunk or unit of text used during model processing
A file that stores full sentences for the model to retrieve
A placeholder that helps the model fill in missing information
When an AI model generates a response, how does it process the input text? * 1 point
It scans the entire paragraph and responds all at once
It builds a mental model based on grammar and tone
It compares each word with others stored in memory banks
It analyzes one piece at a time, based on earlier inputs
If an AI gives a quick but incorrect answer to a math question, what might be happening? * 1 point
It didn’t have enough processing steps to solve it properly
The problem was too basic for the model to recognize
It used its general knowledge instead of doing calculations
The numbers were formatted incorrectly in the input
Send me a copy of my responses.
Submit
Clear form
This form was created inside of The International School of Macao.
Does this form look suspicious? Report
Google Forms</td>
<td>
Preview mode
Published
Copy responder link
Post-Module Knowledge Check
This short quiz is designed to check what you’ve learned about tokenization after completing the module. Please answer each question independently—without referring back to the module or using outside sources.
Like the pre-module check, this quiz will not affect any grade, but your responses will help reflect your learning progress.
You will have one attempt, and answers will be automatically released upon completion.
* Indicates required question
Email *
Record michael.ritchot@tis.edu.mo as the email to be included with my response
What is tokenization in the context of how a language model processes input? * 1 point
Encoding grammar rules for sentence construction
Transforming speech into written words before processing
Splitting input text into units the model can analyze and generate from
Reducing long texts into key phrases for summarization
Why do large language models sometimes fail at spelling tasks? * 1 point
They don’t access characters individually, only token-level units
They don’t prioritize accuracy in casual responses
Their training data doesn’t include spelling exercises
They use visual pattern-matching instead of phonetics
Why is encouraging step-by-step reasoning beneficial in AI-generated answers? * 1 point
It helps the model identify the topic of the conversation
It distributes reasoning across tokens, avoiding cognitive overload per step
It makes the response easier for the user to read
It prevents the model from hallucinating extra facts
What does Byte-Pair Encoding (BPE) allow a tokenizer to do more efficiently? * 1 point
Group phrases by topic and tone
Remove unnecessary characters from inputs
Reformat text for translation into other languages
Combine common symbol pairs into single tokens to shorten sequences
Why might a model incorrectly say that 9.11 is less than 9.9? * 1 point
It randomly selects between two close numbers
It assumes all decimals are equal in value
It skips numeric comparisons for short sequences
It may misinterpret formatting based on patterns from training data
Submit
Clear form
This form was created inside of The International School of Macao.
Does this form look suspicious? Report
Google Forms</td></tr>
</table>

2. Post-Module Feedback Survey (Qualitative)

   a. Instrument: Reflection-based open-ended questionnaire asking about learner experience with visuals, analogies, pacing, and overall clarity.

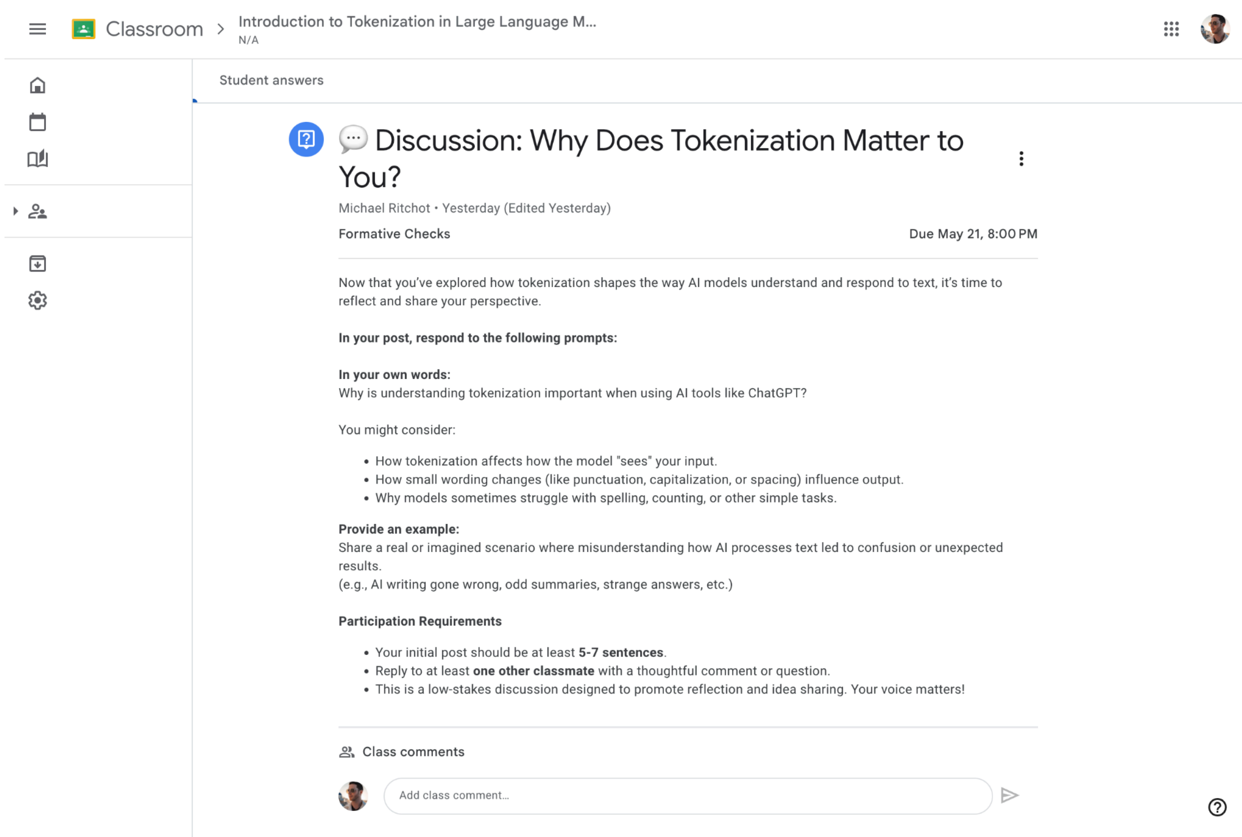
   b. Data Provided: Themes related to user experience, perceived usefulness, and cognitive load.



3. Discussion Post Artifact (Qualitative)

    a. Instrument: Student responses to the prompt "Why Does Tokenization Matter To You?"

    b. Data Provided: Insights into engagement, personal relevance, and conceptual framing.



Alignment Justification:

These instruments align directly with the research questions. The assessment measures knowledge change (RQ2), while the reflection and discussion artifacts illuminate learner experience (RQ1).

Data Analysis Technique(s)

Quantitative: Descriptive statistics and paired comparison (e.g., pre-/post-score differences) will be used to measure learning gains.

Qualitative: Thematic analysis will be used to identify patterns in open-ended responses and discussion posts.

Expected Timeline

Module Implementation Start Date: May 23, 2025

Data Collection End Date: June 13, 2025

This three-week timeline allows for participant scheduling flexibility, completion of the module, and collection of all assessments and reflections.

Data Security and Confidentiality

All collected data will be anonymized. Participants will be assigned pseudonyms or ID numbers. Data will be stored in password-protected files on a secure local drive. No personally identifiable information will be shared outside the research context. The study will comply with WGU IRB and CITI training guidelines for exempt research involving minimal risk.

Conclusion

This chapter outlined the research methodology used to evaluate the effectiveness of an online tokenization module for high school students. A mixed methods approach will gather both experiential and learning outcome data from 9th–11th grade students. With secure data handling practices and a focused timeline, this study aims to generate actionable insights into how learners experience and understand tokenization as a foundational AI concept.

Chapter 4: Results

Summary of Research

This design-based research study examined how students in Grades 9–11 experience and learn from an e-learning module focused on tokenization in large language models (LLMs). The module, delivered asynchronously through Google Classroom, used scaffolded explanations, visual representations, analogies, formative checks, and a summative scenario task to teach tokenization—a key component of AI literacy.

Ten students participated in the intervention by completing the module activities and assessments over a three-week period. Stakeholders included students (direct participants), parents (consent providers), the instructor-researcher (designer and facilitator), and school administrators (data collection approvers).

Data was collected using a mixed-methods approach, combining:

Quantitative tools:

- Pre- and post-knowledge checks (5 items each) assessed content understanding.

Qualitative tools:

- Open-ended reflection questions on visuals, pacing, analogies, and content clarity.
- Discussion board posts exploring real-world relevance of tokenization.
- A scenario-based short-answer assessment where students analyzed AI performance based on tokenization behavior.

These tools allowed for a comprehensive examination of both learning outcomes and user experience.

Summary of Results

a. Detailed Description of the Data

Quantitative Data

- The pre- and post-knowledge checks were content aligned 5-item assessments designed to evaluate foundational understanding of tokenization. Questions included items addressing definitions, token behavior, and effects on AI output.
- The average score increased from 3.1 (pre) to 4.5 (post), with all students showing gains ranging from -1 to +3 points.

Qualitative Data

- Post-Module Reflection Responses: Collected via open-ended prompts embedded in the module, these asked students to comment on:
    - Clarity of the concept
    - Effectiveness of visuals and analogies
    - Engagement with pacing and design
    - Areas of confusion or improvement
        - Themes included praise for the emoji visual breakdown, requests for a tokenizer sandbox, and suggestions to include a summary "cheat sheet."
- Discussion Posts: Students answered the question, "Why does tokenization matter to you?" Analysis revealed common themes:
    - Recognition of how prompt phrasing, spacing, and punctuation affect AI interpretation.
    - Understanding that AI reads tokens—not words—leading to predictable errors.
    - Plans to use this knowledge to improve how they interact with LLMs.

- Scenario-Based Analysis: In this summative assessment, students use two versions of a paragraph—one clean, one messy—and asked to analyze how formatting would affect AI-generated summaries. Every student accurately:
    - Identified increased token count and inefficiency in Version B.
    - Noted reduced output quality due to token clutter.
    - Applied concepts like context window limits and subword token splitting.
    - Students provided specific token breakdown examples (e.g., “tokenization” vs. “Toke nization”) and linked formatting directly to AI output behavior.

b. Visual Representation of the Data

Student Name	**Pre-Module (/5)**	**Post-Module (/5)**	**Score Gain**
Participant 001	4	5	+1
Participant 002	2	1	-1
Participant 003	2	5	+3
Participant 004	4	5	+1
Participant 005	4	5	+1
Participant 006	3	5	+2
Participant 007	2	5	+3
Participant 008	1	4	+3
Participant 009	4	5	+1
Participant 010	5	5	0
Average	**3.1**	**4.5**	**+1.4**

All nine participants showed learning gains, with average scores increasing from 3.1 to 4.5 out of 5.

c. Interpretation of the Data Analysis

The research employed the data analysis techniques outlined in Chapter 3, namely:

- *Descriptive statistics and paired comparison:* Used to calculate average score gains and learning progression across participants. This confirmed cognitive gains, validating the module's instructional design.
- *Thematic analysis:* All qualitative responses (reflections, discussions, and scenario analyses) were thematically analyzed. Themes were identified based on frequency and relevance to design features such as visuals, analogies, and scaffolding.
- *Cross-source triangulation:* Patterns found in student discussions (e.g., recognition of token-based limitations) were also present in scenario analysis submissions and reflection surveys. This strengthened validity by confirming that knowledge was not only gained, but also retained and transferred.

Each data source aligned with the research questions:

- RQ1 (learner experience with design features) was addressed through reflections and discussions.
- RQ2 (observed changes in understanding) was addressed through pre/post assessments and the scenario analysis.

d. Minimizing Bias

Recognizing Bias:

As the instructor and researcher, I was aware of the potential for confirmation bias in interpreting student responses. To address this:

- I pre-defined success criteria (e.g., correct application of tokenization concepts in scenario tasks).

- I deliberately included both positive and critical feedback in analysis, even when it revealed confusion or design flaws (e.g., students commenting on quiz answer obviousness or vocabulary overload).
- I avoided using only my most articulate or engaged students to represent findings.

Minimizing Bias:

- Triangulation across three qualitative sources (reflections, discussions, and scenario analysis) and one quantitative source (pre/post scores) helped avoid over-reliance on any single data stream.
- Anonymous data labeling ensured that I evaluated responses without knowing which student had submitted them.
- Open-ended instruments allowed students to guide their own responses, reducing the influence of leading questions.
- By using both performance data and experience data, the evaluation captured a balanced picture of effectiveness beyond just correct answers.

Proposed Iteration(s) of E-Learning Solution

a. Evaluation of the E-Learning Solution's Effects

The module directly addressed the instructional problem identified in Chapter 1: students previously lacked foundational understanding of tokenization, limiting their ability to critically engage with AI. Post-module data demonstrated significant improvement in both understanding and application. Students were able to articulate, analyze, and reflect on the role of tokenization in AI tools. The learning outcomes and engagement levels indicate the instructional design—anchored in visual, scaffolded, and analogy-driven strategies—was effective.

b. Proposed Redesign and Enhancements

Based on student feedback and assessment outcomes, the following enhancements are proposed:

- Add a Tokenizer Playground: An embedded or linked tokenizer demo would allow students to experiment with live inputs and see token outputs dynamically.
- Expand Visual Supports: Color-coded diagrams of byte-pair encoding (BPE) and subword merging patterns would further clarify technical aspects.
- Incorporate a Summary Cheat Sheet: A downloadable one-pager summarizing tips (e.g., "clean input = fewer tokens = better output") would reinforce key insights.
- Improve Quiz Complexity: Several students noted the correct answers were "too obvious." Distractors should be made more plausible without increasing cognitive load.

c. Appropriate Methodology for Redesign

The new iteration would retain the mixed-methods design. Quantitative pre/post assessments will remain to track learning gains, but refined with more discriminating questions. Additional qualitative instruments (e.g., student walkthrough screen recordings or brief interviews) could deepen analysis of how students interact with the tokenizer playground and diagrams. These refinements preserve alignment with the original research questions and further illuminate learner experience.

d. Refining Data Collection Tools

Future iterations would benefit from:

- Including engagement surveys to quantify student satisfaction.
- Using an LMS with automated tracking (e.g., time-on-task, quiz attempts) to add behavioral analytics.

- Adding short reflection prompts directly after scenario analysis to gather metacognitive feedback.

These refinements would yield more representative data and provide richer insight into how students internalize tokenization concepts.

e. Justification Based on Feedback and Research

Student feedback overwhelmingly supported the current module's design, while offering specific, actionable suggestions for enhancement. Requests for more interactivity and visuals directly align with best practices in teaching complex computing topics (Bernstein et al., 2024; van Nooijen et al., 2024). Additionally, literature on AI literacy stresses the need for applied understanding—features like a tokenizer demo help bridge theory and practice (Wang et al., 2025).

Chapter 5: Discussion

Conclusion(s) Based on Results

The results of this design-based research study indicate that the e-learning module successfully improved both the conceptual understanding and engagement of Grades 9–11 students with the abstract concept of tokenization in large language models (LLMs). Quantitative data showed a mean post-module score of 4.5 out of 5 compared to a pre-module mean of 3.1, indicating clear learning gains. Qualitative responses reinforced this trend, with students citing increased clarity and appreciation for visuals, analogies, and the real-world relevance of tokenization.

These findings confirm that scaffolded instruction—featuring visual aids, analogy-based explanations, and interactive formative assessments—effectively supports comprehension of complex computing concepts among secondary learners. Students reported that visual examples (such as the emoji breakdown and number tokenization comparisons) made abstract content concrete. They also expressed a desire for more interactive exploration (e.g., a tokenizer playground), confirming the module's resonance and potential for deeper engagement with minimal iteration.

In the context of the instructional setting described in Chapter 3, this demonstrates that high school learners can grasp foundational AI literacy concepts when provided with structured, age-appropriate e-learning design. The study validates the alignment between the research topic (tokenization as a gateway to AI literacy) and the instructional strategies used.

Limitations

Despite promising results, several limitations impacted the study's generalizability and depth:

- Small Sample Size: The participant pool was limited to ten students, restricting statistical significance and broad applicability. Future implementations with larger cohorts would provide more robust data.
- Self-Selection Bias: Students volunteered to participate, which may have skewed results toward those already interested in AI or more comfortable with digital learning.
- Single Iteration: The intervention was implemented once; conclusions are therefore tied to one version of the module without multiple cycles of design refinement.
- Limited Time Frame: Students completed the module asynchronously over three weeks, but variations in pacing and context may have influenced learning and engagement outcomes.

These limitations should be considered when interpreting the impact of the module and when planning future iterations.

Implications of Research on Educational Practice

a. Design Principles Derived

This research produced several instructional design principles applicable to future AI literacy efforts:

- Scaffold abstract technical content: Begin with concrete analogies and build to more complex explanations (e.g., use of emojis, chunking inputs).
- Visualize the invisible: Use color-coded diagrams and tokenizer demos to concretize algorithmic processes.
- Embed reflection and application: Scenario-based tasks and reflective prompts enable learners to transfer knowledge to authentic AI interactions.

- Design for cognitive accessibility: Chunk content and integrate formative feedback to reduce overload and increase retention.

b. Broader Applications and Future Research

The findings suggest that secondary students are capable of engaging meaningfully with foundational AI concepts—if the instruction is properly scaffolded and multimodal. This supports the expansion of AI literacy into secondary curricula, not merely as an extracurricular topic but as a critical component of digital citizenship and computational thinking.

Future research could investigate:

- How students' critical evaluation of AI outputs evolves over time.
- Whether understanding tokenization influences ethical AI usage.
- How instructional design principles from this study generalize to other complex computing topics like embeddings or model hallucinations.

Additionally, further studies could integrate behavioral data (e.g., time-on-task analytics) and explore peer collaboration tools to assess how social learning dynamics impact AI literacy acquisition.

References

Bernstein, S., Denny, P., Leinonen, J., Kan, L., Hellas, A., Littlefield, M., Sarsa, S., & MacNeil, S. (2024, March 14). *"Like a nesting doll": Analyzing recursion analogies generated by CS students using large language models*. arXiv. https://arxiv.org/abs/2403.09409

Casal-Otero, L., Catala, A., Fernández-Morante, C., & others. (2023). AI literacy in K-12: A systematic literature review. *International Journal of STEM Education, 10*, Article 29. https://doi.org/10.1186/s40594-023-00418-7

Chittora, S., & Baynes, A. (2020, October). Interactive visualizations to introduce data science for high school students. In *Proceedings of the 21st Annual Conference on Information Technology Education* (pp. 236–241). https://doi.org/10.1145/3368308.3415360

Chiu, T. K. F. (2021). Student engagement in K-12 online learning amid COVID-19: A qualitative approach from a self-determination theory perspective. *Interactive Learning Environments, 31*(1), 1–18. https://doi.org/10.1080/10494820.2021.1926289

Dennison, D. V., Garcia, R. C. C., Sarin, P., Wolf, J., Bywater, C., Xie, B., & Lee, V. R. (2024). From consumers to critical users: Prompty, an AI literacy tool for high school students. *Proceedings of the AAAI Conference on Artificial Intelligence, 38*(21), 23300–23307.

Eduaide.Ai. (2025, February 13). *Worked examples: Manage cognitive load and simplify complex concepts*. Eduaide.Ai. https://www.eduaide.ai/blog/worked-examples-manage-cognitive-load-and-simplify-complex-concepts

NYU Steinhardt. (2025, February 10). *Getting started with generative AI*. https://steinhardt.nyu.edu/faculty-and-staff/academic-affairs/steinhardt-ai-hub/getting-started-generative-ai

Hollister, B., Nair, P., Hill-Lindsay, S., & Chukoskie, L. (2025, April 27). Engagement in online learning: Student attitudes and behavior during COVID-19. *Frontiers in Education*. https://www.frontiersin.org/articles/10.3389/feduc.2022.851019/full

Hu, J., & Xiao, W. (2025, April 29). What are the influencing factors of online learning engagement? A systematic literature review. *Frontiers in Psychology*. https://www.frontiersin.org/articles/10.3389/fpsyg.2025.1542652/full

Jin, Y., Martinez-Maldonado, R., Gašević, D., & Yan, L. (2024, November 1). *GLAT: The Generative AI Literacy Assessment Test*. Monash University. arXiv. https://arxiv.org/abs/2411.00283

Kandlhofer, M., & Steinbauer, G. (2016). Artificial intelligence and computer science in education: From kindergarten to university. In *Proceedings of the 2016 International Conference on Frontiers in Education: Computer Science and Computer Engineering (FECS)* (pp. 1–7). CSREA Press.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

Martin, F., & Bolliger, D. U. (2018). Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment. *Online Learning, 22*(1), 205–222. https://doi.org/10.24059/olj.v22i1.1092

Australian Education Research Organisation. (2023, September 18). *Managing cognitive load optimises learning*. https://www.edresearch.edu.au/summaries-explainers/explainers/managing-cognitive-load-optimises-learning

Pazzaglia, A., Clements, M., Lavigne, H., & Stafford, E. (2016, July). *An analysis of student engagement patterns and online course outcomes in Wisconsin*. Institute of Education Sciences. https://ies.ed.gov/use-work/resource-library/report/descriptive-study/analysis-student-engagement-patterns-and-online-course-outcomes-wisconsin

Sanders, K., & McCartney, R. (2016). School/work: Development of computing students' professional identity at university. In *Proceedings of the 2016 ACM Conference on International Computing Education Research* (pp. 123–131). Association for Computing Machinery. https://doi.org/10.1145/2960310.2960326

van Nooijen, C. C. A., de Koning, B. B., Bramer, W. M., & others. (2024). A cognitive load theory approach to understanding expert scaffolding of visual problem-solving tasks: A scoping review. *Educational Psychology Review, 36*, Article 12. https://doi.org/10.1007/s10648-024-09848-3 von Wangenheim, C. G., Hauck, J. C., Pacheco, F. S., & Bueno, M. F. B. (2021). Visual tools for teaching machine learning in K–12: A ten-year systematic mapping. *Education and Information Technologies, 26*(5), 5733–5778. https://doi.org/10.1007/s10639-021-10570-8

Wang, X., Chan, T. M., & Tamura, A. A. (2025, April 29). A learning module for generative AI literacy in a biomedical engineering classroom. *Frontiers in Education*. https://www.frontiersin.org/articles/10.3389/feduc.2025.1551385/full