FLEX Your MBA: Empowering Learning Efficiency in the Digital Classroom Using an AI-based Application

Piyush Shah[1]; Irita Mishra[2]; Senali Amarasuriya[3]

1 Department of Information Systems, Analytics & Supply Chain, Florida Gulf Coast University, Fort Myers, Florida, USA

2 Department of Management and Marketing, University of Wisconsin–River Falls, River Falls, Wisconsin, USA

3 Department of Management, Middle Tennessee State University, Murfreesboro, Tennessee, USA

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Abstract

The rapid expansion of online MBA programs has improved flexibility and accessibility but continues to face challenges related to limited personalization, reduced interactivity, and summative feedback. To mitigate these issues, we introduce FLEX (Feedback-Linked Education for Excellence), an AI-powered educational platform designed to enhance learning efficiency through dynamic, iterative feedback and active engagement. Developed using R Shiny and integrated with OpenAI's API, FLEX provides a modular, user-friendly scaffolding tool that supports reflective learning, active learning, personalized learning, and formative feedback. Utilizing the Apple Transportation Case, a logistics-focused assignment, FLEX guided MBA students at a large US university through critical decision-making tasks while offering tailored feedback. Results indicated significant improvements in reflective learning, active engagement, personalized learning and formative feedback. This paper also discusses FLEX's potential applications across disciplines and its implications for the future of online education.

Keywords: GenAI, Online education, Active learning, Formative feedback, Logistics

1. INTRODUCTION

The prevalence of online MBA programs has grown substantially over recent years, underscoring their increasing importance in higher education. In the 2018–2019 academic year, 14% of students were enrolled in online MBA programs, a proportion that rose to 28% by 2023–2024 (*Master's Enrollment Trends at AACSB Schools*, 2024). During the 2021–2022 academic year, 47,353 students were enrolled in fully online MBA programs, as reported by AACSB's survey of 288 participating schools, which included both full-time and part-time programs. Notably, flexibility and self-paced learning were key drivers of this growth, with 73% of students in 2022 indicating a preference for studying at their own pace rather than engaging in collaborative virtual projects (Wiley, 2023). Online MBA programs cater particularly to working professionals by offering flexible schedules that enable them to balance academic goals with professional responsibilities. Furthermore, engagement has become a critical factor in academic rankings, accounting for 30% of program evaluations in 2024 (Wiley, 2023). These programs now serve as a comprehensive solution for acquiring the skills necessary for success in today's dynamic job market.

Despite the growing popularity and advantages of online MBA programs, several challenges persist, limiting their effectiveness and impact. A key issue is the lack of personalization, particularly in large classes (Christensen, 2014). While these programs offer flexibility, the content and feedback are often standardized, making it difficult to address the diverse needs of students. Feedback in these programs also tends to be summative rather than formative, focusing on final outcomes without providing actionable insights or opportunities for improvement. Additionally, the structure of online MBA programs often restricts meaningful interaction and critical thinking. Large class sizes and asynchronous environments limit opportunities for collaborative problem-solving and in-depth analysis (Strati et al., 2017), which are essential for developing higher-order thinking skills required in real-world applications. Collectively, these challenges hinder the potential of online MBA programs to fully support and enhance student learning experiences.

Solutions that are implementable in large class settings and those that offer formative feedback and active learning are essential to bridge these gaps and promote equitable learning (Khan et al., 2017). To address these needs, we developed FLEX (Feedback-Linked Education for Excellence)—an interactive platform that leverages Generative Artificial Intelligence (GenAI). FLEX provides personalized, iterative feedback and promotes critical thinking through adaptive learning strategies.

The remainder of this paper is organized as follows. The literature review discusses challenges in online MBA programs and highlights pedagogical frameworks that emphasize reflective learning, active engagement, personalized learning, and formative feedback. The design section outlines the development of FLEX, its technical features, and its application in a logistics (Apple Case) assignment. The results section evaluates the effectiveness of FLEX through statistical analyses of survey data, demonstrating improvements in student engagement and learning outcomes. Finally, the discussion section explores FLEX's contributions to scalable, adaptive learning models and the conclusion provides recommendations for future research and broader implementation.

2. LITERATURE REVIEW

Online MBA programs have gained significant popularity due to their flexibility, allowing students to balance education with professional and personal commitments. However, as mentioned earlier, these programs face challenges including limited personalization, reduced interaction, and perceptions of lower effectiveness compared to classroom-based education. Research highlights that online programs often lack the real-time feedback and collaborative opportunities that facilitate critical thinking and engagement, leading to weaker outcomes in higher-order skills like application and analysis (Arias et al., 2018; Darkwa & Antwi, 2021). Additionally, employers often perceive online degrees as being of lower quality compared to face-to-face programs, which can affect graduates' employability, particularly in hiring decisions for leadership roles (Roberto & Johnson, 2019). Addressing these challenges requires adopting innovative pedagogical approaches that prioritize student engagement, adaptability, and personalized learning. The next section explores how such models are shaping the evolution of online education.

2.1 Online education pedagogy

The development of online education has been influenced by a variety of pedagogical models, reflecting the diverse needs of learners and the rapid advancements in digital technology. Recent frameworks emphasize approaches such as learner-centered design, constructivist methodologies, and situated learning, each contributing to how virtual education environments are structured (Eom & Ashill, 2018; Sorgenfrei & Smolnik, 2016). Adaptive learning systems that tailor content to individual performance illustrate the richness of innovation in this field (Truong, 2016). These models highlight the importance of creating environments that not only deliver content but also actively engage and support learners through personalized experiences.

Despite the diversity among these approaches, it is possible to distill four critical aspects that are central to effective online education: reflective learning, active learning, personalization, and formative feedback (Archambault et al., 2022). These principles encapsulate the need for students to critically engage with content, actively participate in their learning process, navigate personalized pathways suited to their needs, and receive ongoing feedback that facilitates improvement. By adhering to these dimensions, educators and designers can ensure that online platforms create meaningful and impactful learning experiences.

Reflective learning is a cornerstone of effective pedagogy, as it enables students to internalize and critically evaluate their learning experiences (Colomer et al., 2020; Howell, 2021). Reflection helps learners actively connect new knowledge with prior understanding, promoting deeper cognitive engagement (Boyd & Fales, 1983; Bonk & Cummings, 1998). In online education, reflective practices can be integrated through tools such as asynchronous discussion boards, self-assessment prompts, and journaling activities that encourage students to think critically about their learning journey. These mechanisms foster metacognitive awareness, allowing students to develop a more profound understanding of the material.

Active learning is another critical component, positioning students as active participants rather than passive recipients in their educational process (Carr et al., 2015). This involves engaging with materials through problem-solving or collaborations, which leads to the construction of knowledge (Petress, 2008). Online platforms support this by incorporating virtual labs, interactive case studies, and gamified scenarios that require students to apply concepts in authentic and meaningful ways. This engagement ensures that learning is not only retained but also contextualized within real-world applications.

Personalization in online education addresses the diverse needs and preferences of learners by allowing them to engage with content at their own pace, in their chosen environment, and on their preferred device (Murphy et al., 2016). Modern platforms achieve this through adaptive content delivery, tailored recommendations, and flexible learning schedules. Such features enhance accessibility and ensure relevance, promoting sustained engagement across diverse learner profiles. By aligning educational delivery with individual learning styles and preferences, personalization ensures that learners can navigate their educational journeys effectively and efficiently.

Formative feedback supports students by offering timely, constructive, and iterative guidance that fosters self-regulation and reflective learning. In online settings, such feedback ensures that learners receive personalized, actionable suggestions to improve their understanding and performance. By focusing on feedback as a dialogic process rather than mere information transmission, students actively engage in refining their work and building deeper comprehension (Gikandi & Morrow, 2016). Effective formative feedback encourages learners to internalize guidance, adapt their approaches, and progressively align their outputs with desired learning objectives, creating an environment conducive to meaningful and sustained learning engagement.

The integration of reflective learning, active learning, personalization, and formative feedback into online platforms establishes a robust foundation for effective education. These principles, derived from extensive research and practice, serve as a guide for designing tools that are both engaging and impactful. By aligning with these core aspects, online education tools can create transformative learning experiences that meet the needs of diverse learners in an ever-evolving digital landscape.

2.2 Instructional Design Frameworks and FLEX

FLEX is explicitly situated at the intersection of evidence-based instructional design frameworks and AI-driven learning innovation. While established models like Technological Pedagogical Content Knowledge (TPACK) emphasize the critical integration of technological, pedagogical, and content knowledge (Koehler & Mishra, 2009; Swallow & Olofson, 2017), FLEX operationalizes this triad by providing educators with a ready-to-implement platform that inherently balances these dimensions. Unlike TPACK, which remains a conceptual framework, FLEX delivers practical scaffolding that enables instructors to deploy pedagogically sound AI tools without requiring advanced technical expertise, thus bridging TPACK's theory-practice gap.

Similarly, FLEX transcends the SAMR model (Substitution, Augmentation, Modification, and Redefinition), which categorizes technology integration from mere substitution to transformative redefinition (Puentedura, 2006; Blundell et al., 2022). Where many AI tools stagnate at the "substitution" level (e.g., automating quizzes), FLEX achieves "redefinition" by leveraging OpenAI's API to generate dynamic, iterative feedback loops that fundamentally reshape learner-instructor interactions. This enables personalized scaffolding previously unattainable in traditional settings, moving beyond SAMR's descriptive taxonomy to offer actionable redesign of learning workflows.

Crucially, FLEX embeds principles of self-regulated learning (SRL) (Zimmerman, 2002; Theobald, 2021) through its reflective learning modules and iterative feedback design. While SRL theories highlight metacognition and goal setting as keystones of learner autonomy, existing AI tools often neglect structured support for these processes. FLEX addresses this by prompting learners to revise work based on feedback, set improvement goals, and track progress—transforming passive content delivery into active self-regulation cycles.

While existing frameworks like TPACK articulate what educators should achieve in terms of technological-pedagogical integration, and SAMR defines levels of technology adoption, Self-Regulated Learning (SRL) theory underscores why learner agency is fundamental. However, current educational tools seldom integrate all three pillars into a single, accessible, and pedagogically grounded system. FLEX uniquely converges these models to address this gap. It significantly lowers TPACK's technical barriers by enabling extensive customization via simple CSV files without coding, making advanced pedagogical design accessible. It enacts SAMR's highest transformation tier (redefinition) by leveraging AI-driven feedback loops to fundamentally reshape student-instructor interaction and engagement dynamics. FLEX also systematizes SRL principles by embedding mandatory structured reflection within every iterative feedback cycle, actively fostering metacognition and learner autonomy. This synthesis directly addresses the critical unmet need for platforms that concurrently prioritize deep pedagogical rigor, genuinely transformative technology use, and practical, scalable implementation. Therefore, FLEX functions not merely as another educational tool, but as a vital bridge connecting established instructional theory with the practical realities of AI-enabled teaching and learning practice.

2.3 Current applications of AI and GenAI

In recent years, advancements in digital technologies have supported the implementation of pedagogical practices more effectively, with artificial intelligence (AI) emerging as a pivotal enabler of innovative approaches. The application of AI in education dates to Sidney Pressey's "teaching machine" in the 1920s, which provided immediate feedback and automated repetitive teaching tasks, foreshadowing modern Intelligent Tutoring Systems (Holmes & Tuomi, 2022). Today, AI spans domains such as personalized tutoring and administrative automation, offering scalability and efficiency while enhancing student engagement. These systems have significant potential to address challenges like large class sizes and standardized instruction by introducing adaptability and personalization.

Building on the foundational applications of AI in education, generative AI (GenAI) has introduced transformative advancements that address some of the key challenges in online pedagogy. Unlike traditional AI, which focuses on structured tasks such as automated grading and predictive analytics, GenAI dynamically generates content, enabling personalized and adaptive learning experiences. GenAI enhances engagement by tailoring materials to individual student needs, creating interactive simulations, and providing real-time, conversational support (Bozkurt & Sharma, 2023). These capabilities make it particularly effective in fostering critical thinking, reducing transactional distance in online learning, and supporting diverse learner profiles. For instance, GenAI-driven tools can craft customized learning paths and offer immediate, context-aware feedback, ensuring that students remain actively involved in their educational journey (Alasadi & Baiz, 2023). As a result, GenAI has emerged as a vital complement to traditional AI applications, reimagining how online education meets the needs of modern learners.

GenAI has found diverse applications in educational settings, offering practical solutions, such as ChatGPT to provide real-time, adaptive feedback to students in programming courses, supporting their understanding of complex concepts like debugging and algorithm development (Ellis et al., 2024). These tools can act as intelligent tutors, guiding learners through iterative problem-solving while maintaining scalability in large classrooms. Similarly, *CoFee*, developed by Bernius et al. (2022), has demonstrated the ability to support student engagement through machine learning-based feedback mechanisms in large-scale courses. These examples underscore the potential of GenAI to address traditional challenges in online education by blending technological innovation with pedagogical principles.

Despite their potential, existing AI and GenAI tools in education face significant limitations. Many of these tools require substantial technical expertise to design, forcing educators to either become technical experts or rely on expensive, pre-built solutions (Melo, 2023). Additionally, these systems are often narrowly focused, addressing single issues such as grading or teaching specific topics, which limit their adaptability and scalability. Redesigning such tools to meet new objectives typically requires a complete overhaul (Memarian & Doleck, 2023). Ethical concerns, including data privacy, bias, and the misuse of AI-generated content, further complicate their implementation (Holmes & Tuomi, 2022; Lim et al., 2023). AI-generated outputs may perpetuate biases inherent in training data, leading to unfair or inaccurate feedback that reinforces stereotypes or marginalizes certain student groups (Bender et al., 2021). Students may misuse AI tools by over-relying on automated responses for cognitive offloading, undermining metacognitive development and academic integrity (Zawacki-Richter et al., 2019). Data privacy concerns arise when student inputs are processed by third-party AI systems, risking exposure of sensitive information and violating institutional or regulatory standards (e.g., GDPR, FERPA). These challenges—spanning pedagogical integrity, equity, and compliance—highlight tensions between AI's transformative potential and its responsible implementation in learning environments (UNESCO, 2021).

3. DESIGN OF FLEX

FLEX is designed to overcome the limitations of existing AI tools by providing a versatile, accessible, and pedagogically grounded platform. Unlike tools that require extensive technical expertise or focus narrowly on specific tasks, FLEX allows instructors to create interactive and personalized learning experiences with minimal setup effort. By leveraging OpenAI's API for dynamic feedback and incorporating modular components, FLEX ensures scalability and adaptability to a wide range of educational contexts. It bridges the gap between technological innovation and effective pedagogy, making it a transformative tool for online education.

FLEX consists of the R Shiny program (Chang et al., 2024) and six key files, each serving a distinct purpose. Instructors do not need to modify the R Shiny program itself and can use it as is unless they wish to change the master instruction. All necessary configurations can be achieved by editing the six key files, which are simple CSV files that can be modified using any spreadsheet software like Microsoft Excel, along with an optional image file to enhance the app's visual appeal. The six files and their details have been listed in Table 1.

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FLEX's modular design adapts easily to different teaching contexts. Later in this paper, we showcase the app and its integration with the Apple Ocean Shipping application. This includes images and file structure details to clarify their use. The user interface of FLEX is simple and accessible. Built on a Shiny framework, it works across devices, including phones, tablets, and computers, on Windows, macOS, and Android. Questions appear in a scrollable format, allowing students to progress at their own pace. A "*Submit*" button below each question ensures seamless submission. This design minimizes technical barriers, keeping the focus on learning.

3.1 Design features

While there are many important aspects of FLEX's design, this section lists key issues critical to ensuring the application's effectiveness and responsiveness in Table 2.

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FLEX prioritizes privacy by leveraging the OpenAI API, which adheres to strict data security guidelines (*How We Use Your Data*, 2023). Unlike free services such as ChatGPT, data processed via the API is not used to train models, ensuring confidentiality for students and educators. FLEX also emphasizes response authenticity through OpenAI's *temperature parameter*, selected to balance predictability and creativity effectively. This configuration ensures feedback closely aligns with learning objectives while promoting deeper understanding.

Master instruction guides the AI to act as a supportive tutor rather than providing direct answers. It uses constructive prompts to encourage students to revisit and refine their responses, promoting active problem-solving, deeper thinking and metacognitive awareness. For instance, the master instruction avoids fillers and keeps feedback focused on the question, reinforcing goal-oriented learning. FLEX's design ensures that feedback is tailored to each student's input, offering actionable and personalized insights without veering off course. This iterative loop supports students in developing self-regulation and progressively enhancing their skills, ensuring that the feedback process contributes meaningfully to their overall learning journey. The details of the master instructions for the Apple assignment have been explained in section 4.

The easy-to-use interface further enhances learner autonomy and personalization. FLEX allows students to interact with the platform at their own pace, using their preferred devices, and in environments of their choosing. The simplicity of the interface ensures that students can focus on the content and feedback without being hindered by technical complexities. This flexibility not only accommodates diverse learner needs but also empowers students to take ownership of their educational experience, aligning with modern principles of adaptive and learner-centered education. Faculty are encouraged to experiment with this template to adapt FLEX for diverse teaching scenarios, while upholding ethical standards to promote fairness, accountability, and transparency in AI-supported learning environments.

3.2 FLEX and good online teaching practices

The design of FLEX integrates several key features that align with the principles of effective online teaching (Archambault et al., 2022). Among these, the master instruction, the continuous feedback mechanism, and the easy-to-use interface stand out as core elements that address critical aspects of reflective learning, active engagement, learner autonomy, and formative feedback.

By integrating reflective learning, active engagement, personalized autonomy, and formative feedback into its design, FLEX creates a robust platform that aligns with educational research and meets the practical needs of digital learners. Its thoughtful structure transforms theoretical principles into actionable strategies, offering a transformative experience in online education. All these outcomes have been listed in Table 3.

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4. USE CASE (APPLE)

This section examines the use of the FLEX platform in the Apple Transportation Case, a realistic logistics scenario where students assume the role of a logistics manager. Set in April 2019, the case challenges students to decide whether to transport iPhone 11s from China to the United States by air or ocean. Through this scenario, students practice decision-making in operational logistics while applying concepts of cost analysis and transportation efficiency. Students complete this assignment through two interactive applications that together form the Apple case assignment. In the Apple Ocean Shipping application, students calculate the cost per iPhone when shipped using ocean freight and containers. In the Apple Air Shipping application, students determine the cost per iPhone if shipped by air and incorporate inventory-related costs such as holding and lead time impacts. They then compare the two options to arrive at the overall cost and make the best possible shipping decision based on their analysis. This assignment and the applications were developed by the authors.

The Apple Transportation case addresses a gap in logistics education, where operational aspects of transportation are often overlooked in favor of broader strategic discussions. This case dives into the fundamentals of operational logistics, such as palletization, packaging, container stuffing and aircraft specifications, offering students an authentic learning experience. The Apple Transportation case targets multiple levels of Bloom's taxonomy, enabling students to build conceptual understanding, apply quantitative reasoning, and engage in analysis and evaluation. Through structured decision tasks and iterative feedback, the activity promotes learning at the **Understanding**, **Applying**, and **Analyzing** levels.

The learning objectives of this case according to Bloom's taxonomy (Bloom et al., 1956) are:

(a) **Understanding Operational Logistics**: Examining the processes, equipment, and constraints involved in ocean and air transportation, including palletization, packaging, container stuffing, and aircraft specifications (*Bloom level: Understanding*).

(b) **Analyzing Total Logistics Costs**: Evaluating comprehensive costs, including transportation, handling, storage, and delivery, to make informed shipping decisions beyond transportation expenses (*Bloom level: Analyzing*).

(c) **Developing Decision-Making Skills**: Assessing trade-offs between cost, time, and feasibility using decision-making frameworks to optimize transportation choices (*Bloom level: Analyzing*).

(d) **Applying Quantitative Analysis**: Using calculations to analyze shipping costs, capacity utilization, and timelines, enhancing data-driven decision-making abilities (*Bloom level: Applying*).

(e) **Proposing Practical Solutions**: Evaluating real-world logistics scenarios, identifying constraints, and recommending solutions that balance efficiency, cost, and delivery timelines (*Bloom level: Applying/Analyzing*).

The FLEX platform facilitates the Apple Transportation Case by presenting a series of structured questions that guide the student through the decision-making process. Each question corresponds to a specific aspect of the logistics challenge, such as calculating costs, analyzing transportation timelines, or understanding container utilization. Students receive tailored feedback for their responses, encouraging reflection and improvement.

The interaction between the student and the FLEX platform is further facilitated through the use of a carefully crafted system prompt, or master instruction, which governs the behavior of the AI-generated feedback. In the Apple case, this master instruction was iteratively refined and is presented below:

> *"You are a supportive tutor, guiding students through questions and helping them think deeply. Provide feedback only if the student's response is reasonably accurate, shows understanding, or is moving in the right direction. If the response does not meet these criteria, prod the student to try again without giving specific details or hints. Begin*

your response directly, without fillers like 'good start,' and avoid posing any new questions. Focus on addressing the question asked, evaluating if the student has answered it sufficiently, and prodding if necessary to improve their answer. If the student's response is that they don't know or something irrelevant, encourage them to do more research, without providing any specific numbers or ranges. Keep your response focused solely on the current question without introducing new information or guidance on the range unless the answer is within the expected range."

This instructional prompt was developed through close observation of the OpenAI response patterns and calibrated to align with the pedagogical goals of FLEX. Its primary function is to ensure that the feedback remains supportive while upholding academic integrity. Specifically, the instruction is designed to discourage shortcut behaviors such as entering vague or intentionally weak responses (e.g., "I don't know") to receive complete answers from the AI. Instead, it prompts students to engage more deeply with the material. The instruction also limits the scope of feedback to the specific question at hand, thereby reinforcing focus, relevance, and incremental learning without overwhelming the student or deviating from the instructional objective. This deliberate control over AI behavior is critical to maintaining the integrity and educational value of the formative feedback loop within the FLEX platform.

The header for Apple case from a laptop and mobile phone is shown in Figure 1. A sample question and feedback are displayed in Figure 2. The end instructions are shown in Figure 3. The questions file snapshot is shown in Figure 4, and a responses file snapshot has been shown in Figure 5. Figures 1 to 3 highlight the intuitive and visually streamlined user interface of FLEX, while Figures 4 and 5 display a small snippet of the questions and responses files, demonstrating how easily the app can be modified to suit diverse educational needs by changing the questions and the corresponding responses in the CSV files. This attests to the ease-of-use and straightforward structure of the FLEX platform. The detailed questions and responses files are attached to Annexure A.

The response examples provided in Table 4 illustrate how FLEX generates differentiated feedback across varying levels of student responses rather than reacting only to completely incorrect answers. Specifically, the system distinguishes between incorrect, partially correct, and correct submissions and produces correspondingly calibrated guidance. For clearly incorrect responses, the system prompts students to revisit the question or conduct additional exploration without revealing the solution. When answers demonstrate partial understanding, the feedback provides targeted nudges that guide students toward missing conceptual or computational elements. When responses fall within the expected range, the system acknowledges correctness while reinforcing the underlying reasoning.

This graduated feedback structure demonstrates the versatility of FLEX as a pedagogical scaffolding mechanism rather than an automated answer generator. Students cannot bypass the analytical process by submitting minimal or vague responses (e.g., "I don't know") in hopes of extracting the solution from the AI. Instead, the system requires students to iteratively strengthen their responses before receiving confirmatory feedback. In doing so, FLEX preserves the integrity of the learning task while supporting progressive improvement in reasoning and problem-solving. The examples included in the response samples therefore demonstrate how the platform adapts feedback to the strength of student input, reinforcing its role as a structured learning scaffold rather than a substitute for student effort.

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5. RESULTS

We administered the assignment and an anonymous survey to students enrolled in an asynchronous, accelerated MBA program at a large university in the southwestern United States. Of the 58 students who attempted the Apple Case assignment, 50 responded to the survey. After excluding 2 incomplete responses, the final dataset included 48 participants. The demographic details of these participants are presented in Figure 6. Most of the students are between the ages of 18 and 34, studying data analytics or management/leadership with less than ten years of work experience.

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We tested the achievement of four key educational goals highlighted in the paper – reflective learning, active engagement, personalized learning, and formative feedback. The survey instrument was developed *de novo* due to the absence of validated scales capturing self-reported mastery in AI-augmented learning environments. While established instruments assess general educational constructs (e.g., MSLQ for motivation), extant tools fail to measure the unique interplay of dynamic AI feedback, reflective learning cycles, and FLEX-specific competencies such as "critically evaluating AI-generated suggestions" or "applying iterative feedback to revise work." To address this gap, items were derived directly from FLEX's five learning objectives through a structured process:

(a) Operationalizing objectives into observable competencies,

(b) Aligning item phrasing with Bloom's taxonomy verbs (e.g., evaluate, apply, assess) to target intended cognitive levels, and

(c) Iterative refinement by the authors to ensure clarity, relevance, and face validity.

Although target-learner pretesting was infeasible within project constraints, ambiguity was deliberately mitigated through pilot testing with instructional designers ($n = 4$), embedding contextual definitions within survey items, and employing retrospective pretest methodology to anchor pre/post assessments to consistent criteria. While this reflects broader methodological challenges in emergent AI-education research, the scales yielded statistically significant results ($p < .001$). Future psychometric validation remains essential, though the present approach validly captured intervention efficacy given contextual limitations.

The survey included 16 questions based on the Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Shapiro-Wilk tests confirmed that the data was not normally distributed, with p-values less than 0.05 in all cases, rejecting the null hypothesis of normality. This result is consistent with the ordinal nature of Likert scale data, which often deviates from normality due to unequal intervals between categories (e.g., "Strongly Agree" to "Agree") and its bounded structure, leading to skewed distributions or clustering at extremes. Given these characteristics, we employed the Wilcoxon Signed-Rank Test, a non-parametric method suitable for analyzing non-normal, ordinal data (Rey & Neuhäuser, 2011). This test is particularly effective for paired comparisons, such as pre- and post-assignment ratings, and for evaluating whether a dataset's median significantly differs from a neutral value, such as 3 on a 5-point scale. Its flexibility allows for robust analysis across various reflective and formative learning measures.

Students' self-reported mastery of the project's learning objectives was assessed using an anonymous retrospective pretest (post-then-pretest) (Hoogstraten, 1982; Ulmer et al., 2013; Chen et al., 2022). This method simultaneously captures pretest and posttest perceptions via a single instrument administered post-intervention, yielding more accurate estimates of change than traditional pretest-posttest designs (Drennan & Hyde, 2008).

Traditional pretests are susceptible to response shift bias, wherein participants misjudge their initial competence levels due to changing internal standards during the learning process (Cantrell, 2003). Logistics is a specialized field where most students begin with little exposure to concepts like cost analysis, transportation modes, or regulatory frameworks. This is unlike foundational business skills like spreadsheet software, customer service principles, or human resources management, which students either often encounter early or require no specialized starting knowledge. This makes accurate self-assessment of logistics knowledge and skills particularly challenging in traditional pretests. The post-then-pre-evaluation approach enables participants to assess their initial competency levels from their more informed post-training perspective, thereby providing more reliable measurements of learning outcomes. (Pratt et al., 2000).

Additionally, traditional pretests risk sensitization or carry-over effects, potentially inflating change scores by priming participants to course themes (Lam & Bengo, 2002; Chen et al., 2022). In this study, a pretest might have highlighted topics like cost comparisons or operational constraints, altering engagement. By administering assessments solely after the Apple case, the post-then-pre method reduces such biases and grounds results in consolidated understanding.

Limitations include potential recall challenges over extended periods (Pratt et al., 2000), though evidence suggests minimal impact on retrospective accuracy (Townsend & Wilton, 2003). As with all self-reports, results reflect subjective perceptions rather than direct knowledge measurement (Pratt et al., 2000). The anonymous survey format helps mitigate social desirability bias as students honestly report their initial knowledge gaps in the pre-test without worrying about being judged or facing academic consequences. Although this approach requires more time and effort from participants, its advantages in capturing learning gains outweigh the drawbacks, making it the best choice for this study.

The first part of the results, mapped to principles of reflective learning, active engagement, personalized learning, and formative feedback (Q1 – Q16), are presented in Table 5. All questions showed statistically significant differences from the neutral median, indicating positive learning outcomes across the evaluated dimensions.

Within the theme of reflective learning, students reported positive learning experiences, with mean scores of 3.438 (SD = 1.253) for overall experience (Q1) and 3.625 (SD = 1.299) for enhanced understanding of international logistics operations (Q2). Both measures were statistically significant, with p-values of 0.0246 and 0.0044, respectively. The app also supported reflective learning by helping students analyze mistakes and improve (Q3), achieving a mean of

3.6327 (SD = 1.0742) and a p-value of 0.0006, indicating meaningful gains in self-assessment and critical thinking.

Within active engagement, students rated the app as more engaging than traditional assessments, with mean scores of 3.813 (SD = 1.231) and 3.708 (SD = 1.320) for its effectiveness compared to papers (Q5) and multiple-choice tests (Q6), both statistically significant (p = 0.0002 and p = 0.0007). The app's realistic scenarios (Q4) received a high mean of 3.896 (SD = 0.928) and a p-value of 0.0000, demonstrating its success in simulating practical learning contexts. Students also reported that the app made it easier to grasp practical aspects (Q7) (mean = 3.702, SD = 1.283, p = 0.0009) and enhanced engagement (Q8) (mean = 3.5918, SD = 1.1888, p = 0.0022).

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FLEX supported personalized learning through adaptive features for learning pace and guidance (Q9), reflected in a mean score of 3.5102 (SD = 1.0433) and a p-value of 0.0019. Students found the support tailored to their needs (Q10) (mean = 3.449, SD = 1.2258, p = 0.0147) and reported increased confidence in independent learning (Q11) (mean = 3.6327, SD = 1.1672, p = 0.0017). These results suggest the app effectively accommodated individual learning styles and progress.

Within the theme of formative feedback, students valued the app's clear instructions (Q12) (mean = 3.4286, SD = 1.118, p = 0.012) and breakdown of complex tasks (Q13) (mean = 3.6531, SD = 0.9476, p = 0.0001), enabling them to better understand logistics concepts. Feedback was timely (Q15) (mean = 3.7755, SD = 0.9189, p = 0.0000) and targeted areas for improvement without giving away answers (Q14) (mean = 3.6327, SD = 1.1309, p = 0.0009).

Students also reported that the app made learning more structured (Q16) (mean = 3.7755, SD = 1.1949, p = 0.0003), reinforcing formative feedback as a critical component for skill development.

Wilcoxon Signed-Rank tests were conducted using IBM SPSS to assess statistical differences from the median and to compare pre- and post-assessment measures for each topic. The post-then-pretest results are displayed in Table 6. This method collects both pretest and posttest perceptions simultaneously using the same instrument (Drennan & Hyde, 2008; Chen et al., 2022). Here again, the Shapiro-Wilk tests confirmed that the data was not normally distributed, with p-values less than 0.05 in all cases. We employed the paired Wilcoxon Signed-Rank test to compare the pre- and post-test student responses to three questions (Q17 – Q19).

----------------------------- Insert Table 6 Here -----------------------------

The results demonstrate substantial improvements in students' understanding of key logistics concepts and cost analysis (*p-value < 0.001*). For ocean cargo operations, the mean score increased by 46% from 2.125 (SD = 1.347) before the assignment to 3.104 (SD = 1.096) after, with a test statistic of 0.0 and a p-value of 0.000001 (Q17). Similarly, for air cargo operations, the mean score rose by 40% from 2.229 (SD = 1.309) to 3.125 (SD = 1.084), supported by a test statistic of 22.0 and a p-value of 0.000009 (Q18). This indicates a notable improvement in students' understanding of the processes, cost factors, and constraints involved in ocean and air freight operations. In the case of integrated cost analysis for logistics decisions (Q19), the mean score increased by 35% from 2.375 (SD = 1.315) to 3.208 (SD = 1.148), with a test statistic of 10.0 and a p-value of 0.000002. This improvement suggests that students developed stronger analytical skills for evaluating total logistics costs, incorporating transportation, handling, and storage expenses.

The survey also collected student perceptions on the Apple case assignment. Table 7 categorizes student feedback about key learnings based on the four themes of reflective learning, active engagement, personalized learning, and formative feedback. These qualitative responses validate our quantitative findings that iterative feedback and scenario-based problem-solving drive meaningful engagement.

----------------------------- Insert Table 7 Here -----------------------------

6. DISCUSSION

In this paper, we introduced FLEX, a versatile platform designed to enhance online learning and teaching through dynamic, iterative feedback and a modular, user-friendly interface. By leveraging OpenAI's API, FLEX provides educators with an adaptable tool for creating interactive assignments, fostering critical thinking, and addressing pedagogical challenges in diverse educational contexts. We demonstrated FLEX's effectiveness through the Apple Transportation case, a simulated decision related to transporting iPhones from China to the United States. The feedback indicates that while students find the app useful, it also achieves the learning objectives by enhancing their knowledge of logistics and international shipping.

We distilled four key aspects of effective online education from various pedagogical models: reflective learning, active engagement, personalization, and formative feedback (Archambault et al., 2022). FLEX delivers on all these aspects by enabling students to engage in iterative problem-solving, encouraging reflective thinking through dynamic feedback, and allowing educators to tailor content to individual learner needs. Its continuous feedback mechanism ensures that students receive actionable insights to improve their understanding, while the app's intuitive design and flexibility promote active engagement and learner autonomy. By integrating these principles, FLEX provides a robust framework for enhancing online teaching and learning.

FLEX effectively addresses the key limitations of existing AI tools in education by offering a comprehensive, adaptable, and user-friendly platform. Unlike single-issue tools, FLEX is designed to support a wide range of learning objectives across diverse subjects, allowing educators to easily adapt the platform to new scenarios without requiring extensive technical expertise (see Table 8). Its modular design ensures that instructors can modify content by simply editing CSV files or uploading images, eliminating the need for complex programming knowledge.

----------------------------- Insert Table 8 Here -----------------------------

Furthermore, FLEX leverages OpenAI's API with strict privacy controls, ensuring that student data remains secure and protected. By focusing on iterative, context-aware feedback, FLEX supports deep learning and mastery of concepts, bridging the gap between technology and pedagogy. These features collectively make FLEX a scalable and accessible solution, overcoming the challenges of technical complexity, limited adaptability, and privacy concerns in educational technology.

Here, we would like to stress the critical role of the instructor in FLEX. While the platform simplifies and standardizes the process of creating interactive educational content, the instructor remains central to its effectiveness. Instructors design the questions, craft the responses, and shape the feedback tone and language through the master instruction. This approach allows instructors to align feedback with key pedagogical principles such as reflective learning and personalization, ensuring that the technology supports deep engagement and tailored learning experiences. Unlike off-the-shelf packages, which often minimize the instructor's role, FLEX is an instructor-driven tool that empowers educators to adapt the platform to their specific teaching objectives. By placing control in the hands of instructors, FLEX ensures that their expertise shapes the learning experience, reinforcing the importance of active engagement and meaningful feedback in online education.

7. LIMITATIONS AND FUTURE DIRECTIONS

While FLEX significantly enhances accessibility to AI-augmented pedagogy, several limitations warrant consideration. First, instructor proficiency in prompt engineering necessitates iterative refinement of pedagogically effective queries (e.g., "Calculate total landed costs for air versus ocean freight including tariffs"), creating adoption barriers despite template libraries. Second, while FLEX aims to minimize technical barriers through simple CSV configuration, some instructors may still perceive AI integration as technologically intimidating or misaligned with their pedagogical philosophy. Third, time investment in customizing activities and reviewing AI feedback, especially during initial implementation, may deter adoption. Fourth, infrastructural dependencies on OpenAI's API, though cost-effective at ~$0.06/assignment, introduce sustainability risks through potential pricing volatility or service disruptions. Fifth, resistance rooted in concerns about academic integrity or AI reliability may slow institutional uptake. Finally, evaluation scope constraints limit our current assessment to immediate self-reported gains, omitting longitudinal retention, behavioral transfer, and differential efficacy across diverse learner profiles.

Future research should address these limitations through several key initiatives such as including follow-up assessments to evaluate long-term learning outcomes and knowledge application in academic and workplace settings. Such longitudinal designs would help validate whether FLEX fosters durable understanding and transferable skills, strengthening claims about its educational effectiveness. Developing comprehensive faculty training programs for prompt creation and establishing validated measurement scales will strengthen the system's reliability. Testing FLEX in fields beyond logistics will demonstrate its broader applicability, while ensuring the system works fairly for all students remains crucial. Additionally, creating backup systems using different AI models will enhance platform stability. These initiatives will advance FLEX's empirical foundation as a scalable, evidence-informed solution.

8. CONCLUSION

This study highlights the effectiveness of FLEX (Feedback-Linked Education for Excellence) in enhancing learning outcomes in an accelerated MBA program through reflective learning, active engagement, personalized learning, and formative feedback. The results demonstrate significant improvements in students' understanding of logistics processes, cost analysis, and decision-making frameworks, validating FLEX's ability as a scaffolding tool to promote critical thinking and practical skills. By providing an adaptive and interactive platform, FLEX addresses key challenges in online education, offering scalable solutions for large, asynchronous classes. Future research can build on these findings to expand FLEX's applications, assess long-term learning retention, and further integrate AI-driven enhancements to support personalized learning.

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TABLES

Table 1: Key files

Component	Purpose/Function	Key Details
Title File	Allows customization of the app's interface with titles, subtitles, instructions, and optional images.	Blank fields are supported, and an optional image can be added to improve visual appeal.
Student Name File	Includes a one-column list of student names to personalize file saving and submissions.	This file allows easy identification of student submissions for grading purposes.
Questions File	Contains serial numbers and the corresponding question text for the simulation.	Questions should be clearly worded, as instructors will not be present to clarify ambiguities during simulations.
Response File	Maps responses to questions using serial numbers to ensure alignment.	Responses must be correctly paired with questions to maintain coherence and accuracy.
End Instructions File	Provides final instructions for students, such as reminders to download and save work before exiting.	Saving the data is required for the app to function properly, and this file prevents accidental data loss.
Image File	Uploads images to enhance the visual appeal of the app (optional file).	This file improves user engagement and interface aesthetics.

Table 2: Design features

Feature	Purpose	Details
Privacy Protection	Ensures data security through OpenAI's API, which does not use uploaded data for model training.	Provides confidence to educators and students about the safety of their inputs.
Response Authenticity	Uses OpenAI's temperature parameter (set to 0.3) to balance creativity and precision in responses.	Avoids rigid answers while ensuring responses are meaningful and aligned with learning objectives.
Master Instruction	Provides a guiding framework for feedback generation, ensuring constructive prompts and reflective learning.	Customizable template that emphasizes iterative improvement, avoids unnecessary fillers, and encourages students to refine their responses.
Formative Feedback	Incorporates continuous and personalized feedback to support mastery learning.	Helps students identify areas for improvement and strengthens self-regulation skills.
Simple Interface	Designed for ease of use across devices (mobile, tablets, desktops) and operating systems (Windows, macOS, Android).	Allows students to interact seamlessly, scroll through questions, and submit answers at their own pace without technical barriers.

Table 3: Learning outcomes

Principle	Implementation in FLEX	Impact on Learning
Reflective Learning	Uses OpenAI's master instruction to prompt iterative refinement of answers and encourage deeper thinking.	Focus and motivation are sustained as students remain actively involved in improving their current understanding and performance.
Active Engagement	Provides immediate, personalized feedback to help students revise and enhance their answers effectively.	Students develop critical thinking and self-assessment skills by evaluating their responses and making continuous improvements.
Learner Autonomy	Allows flexible, self-paced learning across devices and environments to fit individual schedules and preferences.	Students gain greater independence and versatility, enabling them to take ownership of their learning process.
Formative Feedback	Delivers actionable insights through iterative feedback loops that support continuous improvement.	Learning gaps are identified, and deeper understanding is reinforced through progressive refinement, building confidence and competence.
Adaptability and Scalability	Features modular design and editable templates for easy customization across diverse courses and learning needs.	Students benefit from a flexible system that adapts to varied learning styles, courses, and academic goals.

Table 4: FLEX sample responses

Ocean Shipping Q1:		
A majority of iPhones are made by Apple's supplier, Foxconn, in the Zhengzhou Airport Economy Zone, which is located inland and far from any seaport. Most export zones are typically near seaports. Why do you think China developed this export zone in such a location? Look at the map of China to figure out the location of this region and also search online for the type of factories in this region to help you answer this question.		
1	Wrong answer	China chose this location because land is cheaper inland and factories there mainly produce heavy, low-value goods that are best shipped by trucks instead of ships.
Feedback	*Please explore, search online and try again.*	
2	Partially right answer	The zone was built inland to help develop central China and reduce the focus on coastal regions. It also has a large airport, which helps companies export products more quickly.
Feedback	*TRY AGAIN – Consider why high-value, lightweight products like smartphones are especially suited to air transport, and how their value per unit weight makes proximity to an airport more important than being near a seaport.*	
3	Right answer	The zone targets electronics manufacturing, producing high **value-density** goods like iPhones (high value relative to weight/size), which are best shipped by air—so being near an airport matters more than a seaport. This case illustrates how value density affects logistics choices. Locating the zone inland also helped China promote balanced regional development by boosting growth in central regions.
Feedback	*GOOD ANSWER*	
Ocean Shipping Q2:		
The first step in logistics planning is to understand the physical dimensions and characteristics of the product. So, iPhone 11s are shipped in a box with dimensions 6.61" X 3.66" X 2.05" and the weight of the phones in the box is about 10 ounces. We will work using the metric system. So, I want you to convert the dimensions into millimeters and weight into grams and reply.		
1	Wrong answer	The box dimensions are about 160 cm × 90 cm × 50 cm and the weight is around 3 kilograms.
Feedback	*RETRY – Please use the correct conversion factors (1 inch = 25.4 mm and 1 ounce = 28.35 grams) and convert all three box dimensions and the weight into metric units.*	
2	Partially right answer	Metric dimensions: 167.89 mm × 92.96 mm × 52.07 mm
Feedback	*RETRY – Dimensions look correct; now also convert the weight to grams using 1 ounce = 28.35 grams.*	
3	Right answer	Metric dimensions: 167.89 mm × 92.96 mm × 52.07 mm Metric weight: 283.5 grams
Feedback	*GOOD ANSWER – Your metric conversions are correct and clearly labeled—well done. As an interesting note, only three countries in the world still primarily use the imperial system: the USA, Myanmar, and Liberia.*	

Table 5

Table 5: Findings of the survey based on the principles of reflective learning, active engagement, personalized learning, and formative feedback (n = 48)

Theme	**Survey Question (on a scale of 1 to 5)**	**Mean (SD)**	**Test Statistic (p-value)**
Reflective Learning	Q1. My overall learning experience with the app was positive.	3.438 (1.253)	264.0 (*0.0246*)**
	Q2. The assignment enhanced my learning about international logistics operations.	3.625 (1.299)	217.5 (*0.0044*)***
	Q3. The online app helped me to reflect on my mistakes and understand how to improve.	3.6327 (1.0742)	156.5 (*0.0006*)***
Active Engagement	Q4. The scenario presented in the app was realistic.	3.896 (0.928)	76.0 (*0.0000*)***
	Q5. The online app is more effective than writing a paper for understanding this topic.	3.813 (1.231)	140.0 (*0.0002*)***
	Q6. The online app is more effective than multiple-choice based tests for understanding this topic.	3.708 (1.320)	202.5 (*0.0007*)***
	Q7. The online app made it easier for me to grasp the practical aspects of the topic.	3.702 (1.283)	195.0 (*0.0009*)***
	Q8. I felt more engaged with the learning material because of the online app's interactive guidance.	3.5918 (1.1888)	190.0 (*0.0022*)***
Personalized Learning	Q9. I felt that the online app adapted to my learning pace and provided guidance when I needed it.	3.5102 (1.0433)	134.5 (*0.0019*)***
	Q10. I felt that the online app's support was personalized to my learning needs and progress.	3.449 (1.2258)	235.5 (*0.0147*)**
	Q11. The online app made me feel more confident in my ability to complete learning tasks independently.	3.6327 (1.1672)	151.0 (*0.0017*)***
Formative Feedback	Q12. The online app provided clear instructions that helped me understand the learning tasks.	3.4286 (1.118)	263.0 (*0.012*)**
	Q13. The online app broke down complex tasks or concepts into manageable steps, making them easier to understand.	3.6531 (0.9476)	109.5 (*0.0001*)***
	Q14. The online app provided helpful hints and feedback on where I needed to improve without giving away the answer.	3.6327 (1.1309)	162.5 (*0.0009*)***
	Q15. The feedback from the online app was timely and relevant to my current level of understanding.	3.7755 (0.9189)	51.5 (*0.0000*)***
	Q16. Overall, the online app made the learning experience more structured and manageable for me.	3.7755 (1.1949)	162.5 (*0.0003*)***

*Note: ** and *** indicate statistical significance at the .05 and .01 levels.*

Table 6

Table 6: Findings of the post-then-pretest (n = 48)

Question (Level of Knowledge on a scale of 1 to 5)	**Mean (Std. Dev.)**		
	Pretest	**Posttest**	**Test Statistic (p-value)**
Q17. Understanding the key processes and cost factors involved in ocean cargo operations.	2.125 (1.347)	3.104 (1.096)	0.0 (*0.0000*)***
Q18. Understanding the key processes and cost factors involved in air cargo operations.	2.229 (1.309)	3.125 (1.084)	22.0 (*0.0000*)***
Q19. Using integrated cost analysis to make logistics decisions.	2.375 (1.315)	3.208 (1.148)	10.0 (*0.0000*)***

*Note: *** indicates statistical significance at the .01 level.*

***Table** 7*

Table 7: Student feedback

Theme	Student Feedback on Key Learnings
Reflective Learning	*"I learned about the impact of decisions on long-term results."*
	Considering all the factors and costs that go into transportation and how even though the answer seems obvious, it might not be the most cost-effective.
Active Engagement	*"Using my knowledge of supply chain and how that can be broken down into subsystems."*
	"I believe this concept gets the point across and allows students to do their own research to enhance their learning."
Personalized Learning	*"Engaging activities that are applicable to real life"*
Formative Feedback	*"The [app] taught me about inclusion of various factors I wouldn't have thought of."*
	"I enjoyed these assignments and found the feedback helpful."

Table 8

Table 8: Applicability of FLEX across various disciplines

Discipline	Possible Application
Mathematics	Students can develop algebraic problem-solving skills by starting with simple equations and gradually advancing to complex systems, receiving hints and feedback at each step.
Science	Learners can build an understanding of ecosystems by first identifying food chains and progressively analyzing interactions and environmental impacts.
Programming	Coding platforms can scaffold programming concepts through step-by-step exercises, offering error-specific feedback to help students transition from guided tasks to independent coding projects.
Engineering	Students can design bridges using templates and simulations, moving from basic structural principles to more complex, real-world engineering challenges.
Medicine	Nursing students can practice patient diagnosis by starting with symptom identification and gradually developing treatment plans, supported by iterative feedback.
Business	Learners can develop marketing strategies by analyzing case studies first and then progressing to independent planning, guided by structured frameworks.
Logistics	Students can explore logistics processes step-by-step, beginning with identifying key variables and advancing them to optimizing delivery systems and supply chain networks.
Operations	Learners can enhance process optimization skills by solving basic workflow problems before tackling complex systems, supported by interactive tools and guidance.
Statistics/ Analytics	Students can scaffold statistical analysis skills by starting with descriptive methods and progressing to advanced techniques such as predictive modeling and data interpretation.

FIGURES

Figure 1. Laptop and mobile phone view of the app

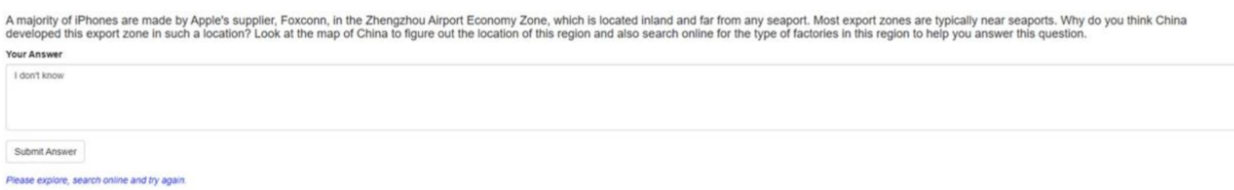


Figure 2. Question and feedback sample

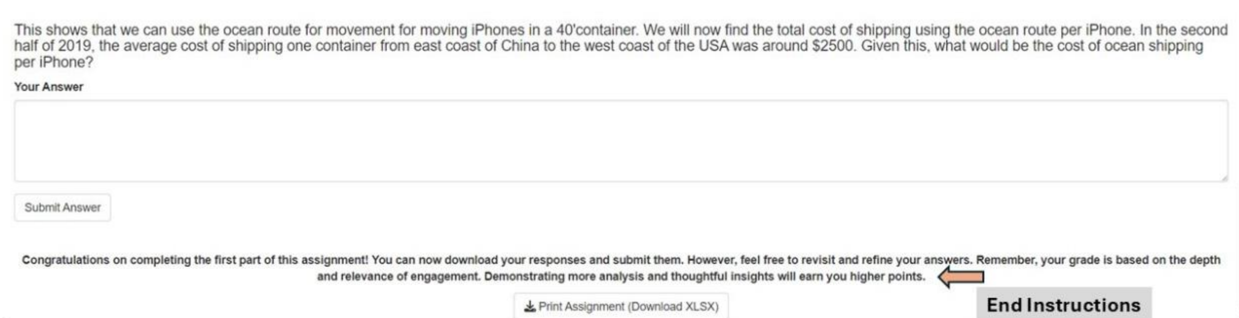
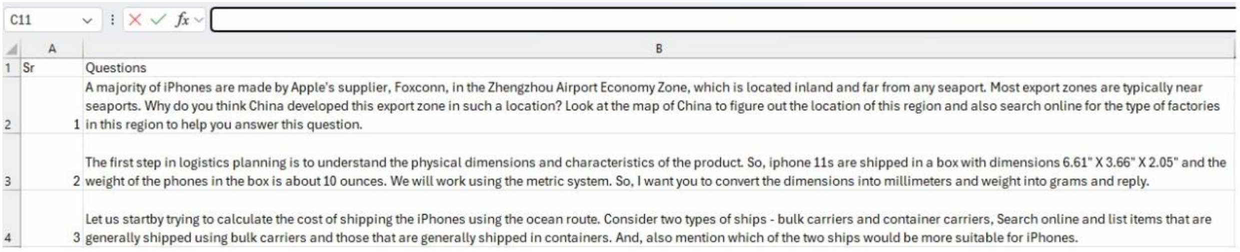


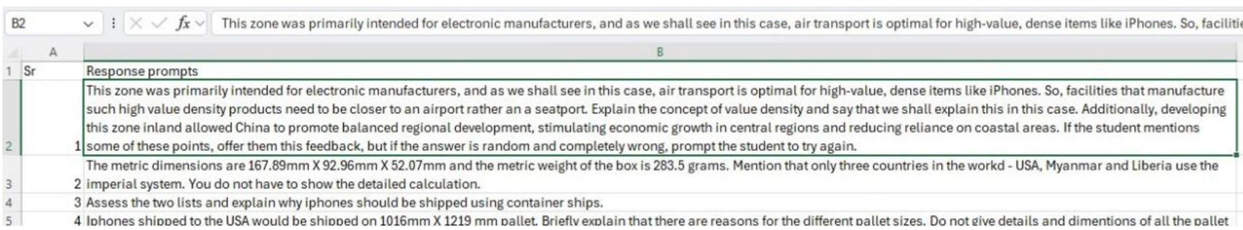
Figure 3. End instructions



C11

	A	B
1	Sr	Questions
2	1	A majority of iPhones are made by Apple's supplier, Foxconn, in the Zhengzhou Airport Economy Zone, which is located inland and far from any seaport. Most export zones are typically near seaports. Why do you think China developed this export zone in such a location? Look at the map of China to figure out the location of this region and also search online for the type of factories in this region to help you answer this question.
3	2	The first step in logistics planning is to understand the physical dimensions and characteristics of the product. So, iphone 11s are shipped in a box with dimensions 6.61" X 3.66" X 2.05" and the weight of the phones in the box is about 10 ounces. We will work using the metric system. So, I want you to convert the dimensions into millimeters and weight into grams and reply.
4	3	Let us startby trying to calculate the cost of shipping the iPhones using the ocean route. Consider two types of ships - bulk carriers and container carriers, Search online and list items that are generally shipped using bulk carriers and those that are generally shipped in containers. And, also mention which of the two ships would be more suitable for iPhones.

Figure 4. Questions file



B2 This zone was primarily intended for electronic manufacturers, and as we shall see in this case, air transport is optimal for high-value, dense items like iPhones. So, facilitie

	A	B
1	Sr	Response prompts
2	1	This zone was primarily intended for electronic manufacturers, and as we shall see in this case, air transport is optimal for high-value, dense items like iPhones. So, facilities that manufacture such high value density products need to be closer to an airport rather an a seatport. Explain the concept of value density and say that we shall explain this in this case. Additionally, developing this zone inland allowed China to promote balanced regional development, stimulating economic growth in central regions and reducing reliance on coastal areas. If the student mentions some of these points, offer them this feedback, but if the answer is random and completely wrong, prompt the student to try again.
3	2	The metric dimensions are 167.89mm X 92.96mm X 52.07mm and the metric weight of the box is 283.5 grams. Mention that only three countries in the workd - USA, Myanmar and Liberia use the imperial system. You do not have to show the detailed calculation.
4	3	Assess the two lists and explain why iphones should be shipped using container ships.
5	4	Iphones shipped to the USA would be shipped on 1016mm X 1219 mm pallet. Briefly explain that there are reasons for the different pallet sizes. Do not give details and dimentions of all the pallet

Figure 5. Responses file

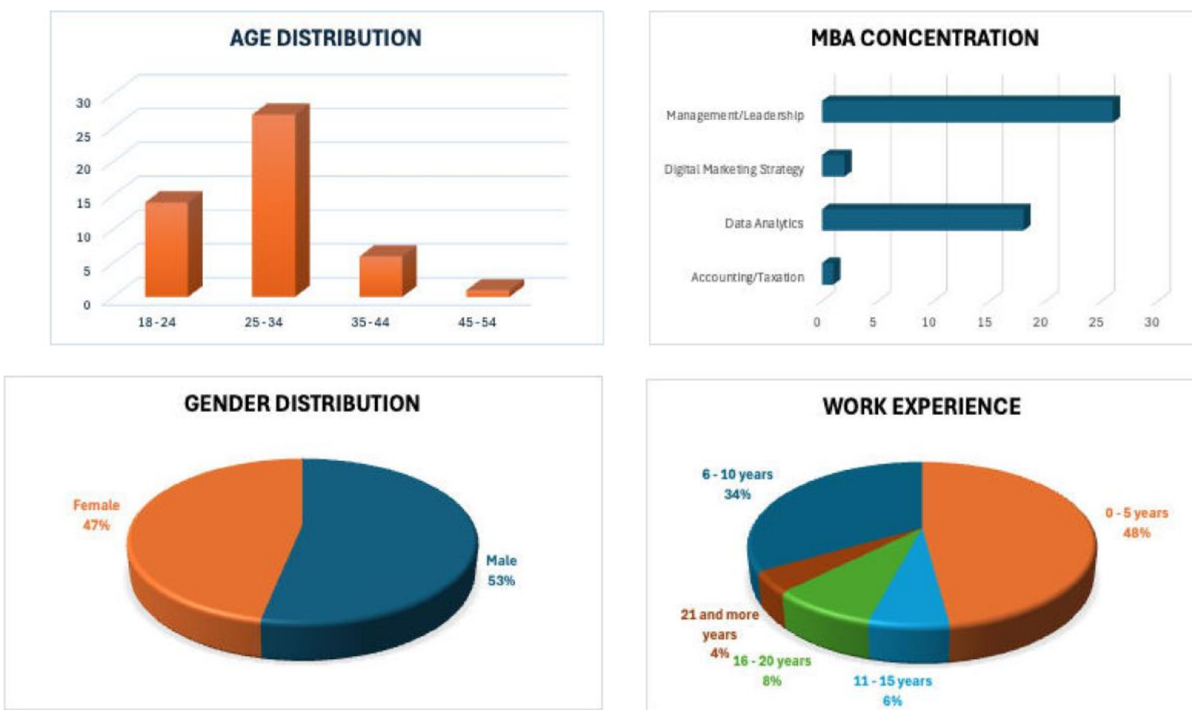


Figure 6. Participants' Demographics