# Scaling Intelligence: Two Years of Institutional Evidence from Los Angeles Pacific University

**Institutional Evidence Report Prepared by:**
George Hanshaw, Psy.D., Director of Digital Learning Solutions, Los Angeles Pacific University

Craig Brewer, Ed.D., Assistant Dean, Los Angeles Pacific University

Shannon Hunt, Professor, Los Angeles Pacific University

Bachelors of Applied Psychology | Masters of Applied Psychology | Criminal Justice

**Date:** January 2026

---

# Abstract

Los Angeles Pacific University conducted a two-year, institution-wide implementation of Spark, a generative AI course assistant, across 99 courses and 225 sections, engaging over 1,300 primarily adult, online learners. Designed as a Socratic, course-embedded AI constrained to instructor-approved materials, Spark functioned as pedagogical infrastructure rather than a stand-alone technology solution, with a central focus on equity, academic integrity, and student belonging.

Across multiple studies, including a randomized controlled trial, large-scale quasi-experimental analyses, and mixed-methods adoption and equity studies, students who engaged with Spark three or more times achieved significantly higher GPAs (mean 3.32 vs. 3.04, $p < .001$, $d = 0.23$), reported higher intrinsic motivation and self-efficacy, and showed particular gains when they entered courses feeling less encouraged, engaged, and supported. Benefits were equitably distributed across race, ethnicity, gender, and age, with no significant interaction effects, suggesting that an intentionally designed, course-bounded AI assistant can operate as an equity lever rather than widen existing gaps. The report concludes that successful AI integration in higher education depends less on technical sophistication than on pedagogy-first design, robust faculty partnership, ethical and privacy safeguards, and continuous monitoring of equity and belonging outcomes, offering a transferable framework for institutions seeking to scale AI responsibly in online learning environments.

# Institutional Evidence Brief – January 2026

A one-page overview for institutional leaders and external partners

### Context and Purpose

- Los Angeles Pacific University (LAPU) is a fully online, Christian-affiliated institution serving ~1,900 primarily nontraditional, diverse adult learners.
- From 2024–2025 LAPU implemented “Spark,” a generative AI course assistant, across 99 courses and 225 sections, reaching more than 1,300 unique students.
- This brief synthesizes two years of institutional evidence on how AI, designed as Socratic, course-embedded pedagogy, can support performance, motivation, belonging, and equity at scale.

### Core Implementation Features

- Pedagogy-first: Spark uses a Socratic approach (questions, hints, scaffolds) and refuses to complete assignments, protecting integrity while deepening learning.
- Course-bounded RAG: Responses draw on each course’s syllabus and materials, aligning AI support with faculty intent and reducing hallucinations and plagiarism risk.
- Equity-by-design: All students see Spark inside the LMS at no extra cost, with adaptive language and 24/7 availability for working adults and ESL learners.

### Key Quantitative Outcomes

- GPA gains: Students who used Spark three or more times earned higher GPAs ($M = 3.32$, $SD = 1.05$) than those with <3 uses ($M = 3.04$, $SD = 1.23$), a 0.28-point difference ($p < .001$, $d = 0.23$).
- Motivation and self-efficacy: In an RCT, treatment students reported significantly higher intrinsic motivation and general self-efficacy than controls, with moderate effect sizes.
- Belonging for at-risk students: Students who initially felt less encouraged, engaged, and supported were more likely to use Spark and subsequently earned higher GPAs, indicating Spark functioned as an equity lever.
- No demographic disparities: GPA gains associated with Spark usage were similar across race, ethnicity, gender, and age, with no significant interaction effects detected.

### Key Qualitative and Adoption Insights

- Students described Spark as a safe space to test ideas, clarify difficult concepts, and build confidence before posting in class.
- Non-use was driven primarily by low perceived need and limited awareness, not by dissatisfaction with Spark’s quality or reliability.
- Faculty stance mattered: courses where instructors modeled Spark, integrated it into activities, and framed it as a learning partner saw substantially higher adoption.

### Strategic and Ethical Commitments

- AI is positioned as pedagogical infrastructure that augments, not replaces, human teaching and success coaching, and is integrated into a broader “belonging ecosystem.”
- Data practices prioritize FERPA compliance, psychological safety (no instructor access to individual chats), and transparent communication about data use.
- Ongoing work focuses on bias auditing, digital literacy support, and monitoring long-term impacts on student–faculty relationships.

### Implications for Other Institutions

- Treat AI as a teaching and equity strategy, not merely a technology purchase; anchor design in local mission, pedagogy, and student demographics.
- Start with a well-designed pilot (ideally with experimental or quasi-experimental evaluation), then scale in waves with strong faculty leadership and communication.
- Integrate AI into coursework and professional development, track outcomes by demographic group, and build governance structures that keep ethics, equity, and human connection at the center.

## Purpose of This Report

This report synthesizes two years of research, implementation, and evaluation of AI course assistants at Los Angeles Pacific University (LAPU). Rather than presenting a single study or advocating for a specific technology solution, this document integrates findings from randomized controlled trials, quasi-experimental analyses, mixed-methods studies, and design cases to provide a coherent institutional account of how AI can function as pedagogical infrastructure in online higher education.

The primary purpose of this report is to make LAPU's work legible and useful to other colleges and universities that are grappling with questions about AI adoption, instructional integrity, equity, and scale. It is written for academic leaders, faculty developers, instructional designers, and institutional researchers who are seeking evidence-informed guidance grounded in real-world implementation rather than speculative promise.

## Why This Report Was Created

Since the public release of generative AI tools in late 2022, higher education institutions have faced significant pressure to respond, often quickly and without clear models to follow. Many early conversations focused on academic integrity risks, policy compliance, or tool prohibition. LAPU chose a different path: to study AI as a teaching and learning practice, not merely a technology problem.

Over a two-year period, LAPU implemented AI course assistants across nearly all online courses and evaluated their impact on academic performance, motivation, belonging, and equity. As results accumulated across multiple studies, it became clear that no single article or design case fully captured the scope of what was learned. This report was created to bring that work together into a single, accessible institutional narrative.

## What This Report Is, and Is Not

This document is best understood as an institutional evidence report. It is not a marketing white paper, a vendor evaluation, or a prescriptive blueprint that assumes one-size-fits-all adoption. It does not claim that LAPU's approach should be replicated wholesale by other institutions.

# Instead, this report offers

- A synthesis of empirical findings across multiple studies
- A transparent account of design and implementation decisions
- Evidence of what changed when AI was embedded as part of pedagogy
- Reflections on challenges, limitations, and unresolved questions

Readers are invited to adapt, not adopt, the practices described here in ways that align with their own institutional missions, student populations, and governance structures.

# How to Read This Report

Different readers may engage with this report for different purposes:

- Institutional leaders may focus on outcome summaries, equity findings, and lessons learned for scaling.
- Faculty developers and instructional designers may focus on sections related to pedagogy, faculty engagement, and course-level integration.
- Researchers may focus on study design, analytic approaches, and limitations.

The report is structured to allow selective reading, with each major section designed to stand on its own while contributing to a cohesive whole.

# Executive Summary

In March 2024, Los Angeles Pacific University (LAPU), a fully online, faith-based institution serving nearly 1,900 primarily nontraditional adult learners, launched Spark, a Generative AI (GenAI) course assistant, in just four weeks. Over the subsequent two years, this implementation has evolved from a pilot program into a comprehensive, institution-wide ecosystem that now serves students across 99 distinct courses and 225 sections, engaging more than 1,300 unique students across both undergraduate and graduate programs[1].

This report synthesizes the outcomes of two years of full-scale AI integration in online higher education, documenting what we have learned about the potential and challenges of embedding AI as a core pedagogical partner in student learning. Our research demonstrates that AI course assistants, when intentionally designed and ethically implemented, can significantly improve academic performance, enhance intrinsic motivation, and foster a greater sense of belonging among historically underserved learners without widening existing equity gaps.

## Key Findings

- **Academic Performance:** Students who engaged with Spark three or more times achieved significantly higher GPAs ($M = 3.32$, $SD = 1.05$) compared to non-users ($M = 3.04$, $SD = 1.23$), with a mean difference of 0.28 points ($p < .001$, Cohen's $d = 0.23$)[1].

- **Intrinsic Motivation and Self-Efficacy:** Treatment group students reported enhanced intrinsic motivation and general self-efficacy with moderate effect sizes observed, suggesting AI assistants help students develop greater confidence in their academic abilities[2].

- **Equitable Access:** Across demographic groups—including race, ethnicity, gender, and age—benefits of AI assistance were equitably distributed, with no significant disparities in outcome gains[3].

- **Sense of Belonging:** Students who reported lower baseline feelings of engagement, encouragement, and support were more likely to use Spark and subsequently earned higher GPAs, indicating AI assistants serve as equity levers for at-risk students[4].

- **Barriers to Adoption:** While 602 surveyed students confirmed AI benefits, perceived necessity (lack of perceived need), limited awareness, and unfamiliarity remain primary barriers to adoption, rather than dissatisfaction with the tool itself[5].

## Strategic Implications

Our institutional experience demonstrates that successful AI implementation in higher education requires far more than technical deployment. It demands intentional pedagogical design, faculty partnership, clear communication, and ongoing attention to ethics and equity. The evidence presented in this report offers a roadmap for other institutions seeking to harness AI in ways that strengthen—rather than diminish—human-centered, student-centered learning.

# Introduction: The AI Imperative in Higher Education

The landscape of higher education has shifted dramatically since the release of ChatGPT in November 2022. That pivotal moment forced institutions worldwide to ask fundamental questions: How do we harness this technology responsibly? Can AI enhance learning, or does it undermine academic rigor? Who has access to these tools, and might they exacerbate existing inequities?

At LAPU, we chose not to restrict generative AI. Instead, we asked: How might we harness this technology in a way that supports deeper learning, safeguards academic integrity, and reflects our radically student-centered mission?[6]

This question became the north star guiding our two-year journey of AI integration.

## Context: LAPU's Institutional Mission

LAPU is a fully online, Christian-affiliated institution serving approximately 1,900 students across undergraduate and graduate programs. Our student population is notably diverse and nontraditional:

- **61.2% part-time enrollment** (students balancing education with work and family)
- **Predominantly female:** 81% identify as female; 17.4% as male; 1.5% chose not to state
- **Highly diverse:** 46% Hispanic of any race; 17% Black or African American; 20% White; 7% Asian; 5% two or more races; 1% Native Hawaiian or Pacific Islander; <1% American Indian or Alaska Native

Our institution's commitment to access and affordability makes us a beacon for working adults and first-generation learners who might not have pathways to traditional residential education. Yet the asynchronous, online format that enables this access also creates profound challenges: limited real-time interaction, reduced peer connection, and uneven access to individualized academic support.

This is the problem AI was designed to address: at scale, equitably, and ethically.

Our hope is that this work positions LAPU's experience as a model for responsible AI innovation in higher education while acknowledging the complexity of translating potential into sustained, equitable outcomes.

---

# Part 1: Research Overview and Theoretical Framework

## 1.1 The LAPU AI Ecosystem: Overview of Studies Conducted

Over two years, LAPU has generated multiple complementary studies examining AI's impact from different angles:

**Study 1: The Pilot Randomized Controlled Trial (RCT)**
In Spring and Summer 2024, a randomized controlled trial involving 92 students across two courses (BIBL 230: Biblical Literature and PSYC 105: Introduction to Psychology) compared students with access to Spark to a control group without access[2]. This pilot established the causal foundation for subsequent expansion.

**Study 2: Full Implementation Quasi-Experimental Study (2024-2025)**
Following positive pilot results, a large-scale quasi-experimental study analyzed 2,090 unique student-course combinations and 1,338 unique students across 99 courses and 225 sections[1]. Using nonparametric statistical methods (Mann-Whitney U-test, Wilcoxon signed-rank test) and propensity score matching to control for confounding variables, this study provided robust evidence of AI effectiveness at scale.

**Study 3: Barriers and Adoption Study**
A mixed-methods exploratory study analyzed 602 End-of-Course (EOC) survey responses using sentiment analysis and thematic analysis to understand why some students chose not to use Spark[5]. This study was critical for identifying improvement opportunities.

**Study 4: Belonging and Equity Analysis**
An analysis of survey responses across courses examining how AI intersects with students' sense of belonging, engagement, encouragement, and support—with particular attention to whether AI benefits were equitably distributed across demographic groups[4].

**Study 5: Implementation and Design Case Study**
A design case documenting the rapid four-week rollout process, pedagogical decision-making, and the evolution of Spark's role in the learning ecosystem[6].

## 1.2 Theoretical Foundations

These frameworks are presented not as theoretical requirements, but as lenses that helped us interpret what we were seeing institutionally. They informed how we made sense of adoption patterns, student experiences, and outcomes as the implementation scaled, rather than serving as prescriptive models that faculty or institutions must adopt.

Our approach to AI implementation was grounded in several complementary theoretical frameworks:

**Gabriel's Behavioral Engineering Model (BEM)**
The BEM provided a lens for examining the institutional conditions necessary for successful technology adoption. Rather than assuming a tool would simply improve outcomes by existing, we asked: What environmental factors, feedback mechanisms, incentives, and support systems enable adoption? This framework guided our phased rollout and emphasis on faculty partnership[6].

**Socratic Method and Constructivism**
Spark was explicitly designed to mirror the Socratic method, asking clarifying questions rather than providing direct answers. This approach is rooted in constructivist learning theory—the idea that knowledge is actively constructed by learners through reflection and dialogue, not passively received[6]. By refusing to complete assignments for students, Spark encourages deeper cognitive engagement.

**Tinto's Model of Student Retention**
Tinto's framework emphasizes that students persist when they experience both academic and social integration. Spark was positioned as a tool for academic integration, reinforcing course norms, expectations, and providing just-in-time support even in asynchronous contexts[4].

**Maslow's Hierarchy of Needs**
Belonging is a foundational prerequisite for motivation and achievement in Maslow's hierarchy. Spark was designed not merely to deliver answers but to convey to students that their questions are valid, their learning matters, and help is always available—critical psychological messages in online environments where isolation is common[4].

**Community of Inquiry (CoI) Framework**
The CoI framework identifies three essential presences in effective online learning: cognitive (thinking and learning), social (feeling connected and safe), and teaching (instructor presence and guidance). Spark contributes to cognitive presence through prompting reflection and scaffolding understanding; it also enhances teaching presence when faculty frame it as a pedagogical partner[4].

## 1.3 The Equity Imperative

At the center of our AI strategy was an unwavering commitment to equity. This commitment operated at multiple levels:

**Equity as Access:** All students had equal access to Spark at no additional cost, integrated directly into the learning management system (LMS) with no external login required.

**Equity as Differentiation:** Spark was designed to adapt to diverse learner needs—adjusting language complexity for ESL students, offering multiple forms of explanation, and providing 24/7 support for students whose work schedules made office hours impossible.

**Equity as Representation:** We prioritized recruiting faculty from diverse backgrounds to participate in AI literacy development and implementation leadership, ensuring that diverse pedagogical perspectives shaped Spark's design.

**Equity as Outcome:** We committed to measuring whether AI benefits were equitably distributed. Our hypothesis was that well-designed AI could function as an equity lever—particularly benefiting students with lower baseline support and engagement[3].

---

# Part 2: Research Findings

## 2.1 Academic Performance Outcomes

**Research Question:** What is the impact of an AI course assistant on student GPA?

**Hypothesis:** Students who utilized Spark three or more times would achieve significantly higher GPAs than those who utilized it fewer than three times.

### 2.1.1 Quantitative Results

The quasi-experimental study analyzing 2,090 student-course combinations revealed compelling evidence of positive academic impact[1]:

- **Treatment Group (3+ uses):** M = 3.32, SD = 1.05
- **Control Group (<3 uses):** M = 3.04, SD = 1.23
- **Mean Difference:** 0.28 points
- **Statistical Significance:** $p < .001$
- **Effect Size (Cohen's d):** 0.23 (small-to-moderate effect)

These results held robust when controlling for confounding variables through propensity score matching and permutation analysis. The effect was observed consistently across:

- **All demographic groups:** No significant interactions between AI usage and race, ethnicity, gender, or age
- **Multiple course types:** Across 99 distinct courses spanning diverse disciplines
- **Different student populations:** Both traditional undergraduate and working adult learners; term-based and competency-based students

### 2.1.2 Why Did AI Improve Grades?

Our research identified several mechanisms:

**1. Just-In-Time Support**
In asynchronous online education, students often encounter confusion at moments when instructors are unavailable. Spark provides immediate, personalized assistance, answering questions and scaffolding understanding without completing assignments. This immediate feedback loop allows students to address conceptual gaps before completing work.

**2. Socratic Scaffolding**
Rather than providing answers, Spark guides students through a thinking process. One student reflected: "Spark doesn't do the work for you. Spark asks me questions on what I already know and it was like Spark and I did the work together."[4] This approach promotes deeper understanding and stronger retention than direct instruction alone.

**3. Personalized Pacing**
Spark adapts its language complexity, examples, and explanation depth to individual students. For ESL learners and students with learning differences, this adaptability was particularly powerful.

**4. Reduced Cognitive Load and Increased Confidence**
By having a responsive learning partner available, students reported reduced anxiety about getting "stuck." This confidence boost translated into greater willingness to tackle challenging material.

### 2.1.3 The Role of Frequency

Notably, the threshold of "three or more interactions" emerged as significant. Our analysis suggests this reflects a learning curve: the first interaction may be exploratory, the second may be clarifying, and by the third, students understand Spark's value and how to use it effectively. This threshold has implications for communication and onboarding strategies.

## 2.2 Motivation and Self-Efficacy

**Research Question:** Does AI assistance affect intrinsic motivation and students' confidence in their academic abilities?

### 2.2.1 Intrinsic Motivation

Intrinsic motivation—the internal drive to engage in learning for its own sake—is a key predictor of academic persistence, especially in asynchronous environments where external motivation is limited[2].

The pilot RCT measured intrinsic motivation using validated scales. Students in the treatment group reported significantly higher intrinsic motivation compared to the control group, with moderate effect sizes. Qualitative feedback reinforced this finding:

- "Talking to Spark gave me the courage to share my real opinion. By the time I posted, I knew I had already tested my idea in a safe space."[6]
- "I used Spark when I did not understand what I was reading. And when Spark explained the difficult concept for me, I finally understood."[4]

These reflections suggest that Spark enhanced motivation through:

- **Psychological Safety:** Students felt comfortable exploring ideas without judgment
- **Clarity:** Students better understood what they needed to learn
- **Sense of Progress:** Immediate feedback conveyed that their efforts were moving them forward

### 2.2.2 Self-Efficacy

Self-efficacy—an individual's belief in their capacity to succeed—is strongly correlated with academic performance and persistence[2]. The pilot study measured general self-efficacy using the Schwarzer & Jerusalem General Self-Efficacy (GSE) scale.

Results indicated a significant positive impact on self-efficacy, suggesting that AI course assistants can enhance students' confidence in their academic abilities. Mechanisms included:

- **Accessibility of Support:** 24/7 availability reduced anxiety about seeking help
- **Responsive Feedback:** Immediate reactions conveyed that assistance was available
- **Inclusive Interaction:** Spark's non-judgmental approach (never expressing frustration or impatience) was particularly important for students with prior negative academic experiences

## 2.3 Belonging and Emotional Support

**Research Question:** Does AI assistance affect students' sense of belonging, particularly for those with lower baseline connection to their courses?

### 2.3.1 The Paradoxical Finding

One of the most interesting and initially counterintuitive findings emerged from an analysis of student survey responses on three measures: encouragement, engagement, and support[4].

At first glance, the data suggested a troubling pattern: Students who used Spark reported lower mean scores on these measures compared to non-users:

- **Encouragement:** AI users M = 4.41 vs. non-users M = 4.54 ($p < .001$)
- **Engagement:** AI users M = 4.39 vs. non-users M = 4.52 ($p < .001$)

- **Support:** AI users M = 4.43 vs. non-users M = 4.52 ($p < .001$)

However, further analysis revealed the critical insight: The causality runs in the opposite direction. Students with lower baseline feelings of encouragement, engagement, and support were more likely to use Spark, not the reverse.

This was profoundly important because it reframed AI's role: Rather than diminishing student experiences, Spark served as an equity intervention for students already at risk of disengagement.

### 2.3.2 The Belonging Ecosystem

The data revealed that students who used Spark and initially felt less encouraged, engaged, and supported subsequently earned higher GPAs. This suggests that Spark contributed to their academic success in measurable ways, which in turn likely enhanced their emotional experience.

The research team concluded that Spark functions as part of a broader "belonging ecosystem" at LAPU—which includes:

- Faculty-student interaction and course design
- Success coaching (weekly personalized support from dedicated student success coaches)
- Peer connection and discussion boards
- Institutional support services
- **AI assistants as a scalable, 24/7 extension of this ecosystem**

Rather than replacing human connection, Spark bridges moments when human support is unavailable. For working adults juggling jobs, families, and school, these bridges are critical.

## 2.4 Equity Outcomes

**Research Question:** Are the benefits of AI assistance equitably distributed across demographic groups?

### 2.4.1 No Demographic Disparities

One of the most important findings from the follow-up analysis was this: **Students of different races, ethnicities, genders, and ages experienced similar gains in GPA when using Spark, with no statistically significant interaction effects between AI usage and any demographic variable**[3].

This finding was remarkable given longstanding equity gaps in higher education. In fields like computer science and engineering, gender gaps in performance exist; in many contexts, racial and ethnic achievement gaps persist. Yet Spark's benefits were democratically distributed.

**Why might this be?**

Several design choices may explain equitable outcomes:

1. **Non-Discriminatory Access:** Spark is embedded in the LMS with no barriers to entry. Students don't need to "opt in" to special programs; it's simply there.

2. **Culturally Responsive Design:** Spark was trained not to make assumptions about student backgrounds or cultural contexts. Its Socratic questioning approach is deliberately universal rather than culturally specific.
3. **Accessibility Features:** Spark's ability to adapt language complexity and adjust for diverse learners (including ESL, neurodivergent, and students with learning disabilities) meant no demographic group was left behind.
4. **Integration with Existing Support:** Spark enhanced—rather than replaced—LAPU's already-strong student success coaching model, which was designed with equity at its center.

### 2.4.2 Implications for Scaling

These findings suggest that well-designed AI can function as an equity lever in higher education. This is not inevitable; it requires intentional design. An AI assistant that reflects biases in its training data, that is not accessible to students with disabilities, or that is only available to students who opt into premium services could easily widen gaps.

Our experience shows that the alternative is possible.

## 2.5 Barriers to Adoption

Despite compelling evidence of benefits, not all students used Spark. Understanding why is crucial for maximizing impact.

### 2.5.1 Mixed-Methods Barrier Analysis

A mixed-methods analysis of 602 student survey responses identified the primary reasons for non-use[5]:

**1. Perceived Necessity (Lack of Perceived Need)** – MOST SIGNIFICANT

- Many students felt they understood the course content without additional support
- Some assumed tutoring services (human or AI) were for struggling students, not for them
- Others didn't recognize that Spark could assist with study strategies, exam preparation, or writing

**2. Lack of Familiarity and Awareness** – SUBSTANTIAL

- Some students were unaware Spark existed
- Others had heard of it but didn't understand its functionality or how to use it
- A few confused Spark with other campus resources

**3. Preference for Traditional Learning Methods** – MODERATE

- Some students preferred face-to-face interaction or didn't feel comfortable with AI
- Others relied on textbooks, notes, or traditional study groups
- Time constraints and competing priorities meant some didn't explore new tools

**4. Technical or Trust Barriers** – MINOR

- Unlike many technology adoption studies, dissatisfaction with the tool itself was rare
- The absence of negative sentiment suggested resistance wasn't rooted in Spark's quality but in limited perceived value or awareness

### 2.5.2 Critical Insight: Not a Quality Problem

The most encouraging finding: **None of the non-users expressed negative sentiment about Spark's quality or reliability.** They weren't avoiding it because it didn't work; they weren't using it because they didn't perceive the need or weren't aware of its potential.

This distinction is important because it points to solutions: Better communication, faculty modeling, integration into coursework, and digital literacy initiatives could meaningfully increase adoption.

## 2.6 Faculty Implementation and Pedagogical Integration

**Research Question:** How does faculty engagement shape student adoption and outcomes?

### 2.6.1 The Role of Faculty Presence

Our research revealed that instructor stance significantly influenced student adoption of Spark. Faculty who:

- **Modeled Spark use** (showing students how they might use it)
- **Integrated Spark into course activities** (e.g., Think-Pair-Share with Spark as the "pair")
- **Framed Spark as a learning partner** (not a cheating tool or inferior substitute for real tutoring)
- **Demonstrated trust** in Spark through their own positive stance

...had substantially higher student adoption and engagement rates.

Conversely, faculty who expressed skepticism or mentioned Spark only in passing saw minimal usage.

### 2.6.2 Active Learning Integration

The most innovative implementations embedded Spark into active learning strategies[6]:

**Think-Pair-Share with Spark:**
Students think about a question individually, then discuss their thinking with Spark (receiving Socratic prompts), then share refined ideas with their peers. This format transformed Spark from a reactive Q&A tool into a proactive thinking partner.

**Role-Play Simulations:**
Spark took on the voice of historical figures, fictional characters, or professionals in a field. Students interviewed, negotiated, or debated with Spark—practicing communication skills in realistic scenarios.

**Scaffolded Reflection:**
Faculty embedded Spark-guided reflection prompts into assignments. Rather than just asking

"What did you learn?", students answered Spark's probing questions about their understanding, application, and transfer.

These integrations changed the conversation about Spark from "Is this tool useful?" to "Spark is part of how we learn together in this course."

---

# Part 3: Design, Implementation, and Ethical Considerations

## 3.1 Pedagogical Design: The Socratic Approach

Why did we choose the Socratic method for Spark's interactions?

**Academic Integrity:** A direct answer to an assignment question is plagiarism if submitted as the student's own work. By refusing to complete assignments, Spark maintains clear ethical boundaries while still providing support.

**Deeper Learning:** Socratic questioning activates prior knowledge, surfaces misconceptions, and prompts metacognitive reflection. Students who articulate their thinking develop stronger understanding than those given direct answers.

**Student Agency:** The Socratic approach respects student autonomy. Rather than being passive recipients of information, students become active participants in their own learning.

**Scalable Human-Like Interaction:** A chatbot that gives answers is less impressive than a human tutor; a chatbot that asks thoughtful questions can rival human tutoring in many contexts.

### 3.1.1 Implementation Through Prompting

Spark's behavior is shaped by a hierarchical system prompt containing[6]:

1. **Role Definition:** "You are a teaching assistant who uses the Socratic method"
2. **Core Rules:** "Do not generate assignment answers," "End every response with a question," "Offer hints before explanations"
3. **Examples of Allowed Responses:** Short clarifications, analogies, guiding questions
4. **Examples of Prohibited Responses:** Full assignment responses, unverified claims, direct citations outside course documents
5. **Self-Check Instructions:** Spark is prompted to verify its own compliance before replying

This level of specificity in prompting proved essential. Without clear constraints, even well-intentioned LLMs can drift toward providing answers.

## 3.2 Retrieval-Augmented Generation (RAG) and Course-Specific Knowledge

A critical design decision was using Retrieval-Augmented Generation (RAG) to constrain Spark's knowledge[1].

**What is RAG?** RAG is a technique that improves LLM outputs by integrating information from external documents. Rather than relying on its general training data, Spark retrieves relevant information from a course's syllabus, readings, and materials before responding.

**Benefits for Academic Integrity:**
By referencing only course-approved materials, Spark avoids providing outside information that a student might plagiarize. Spark can say, "Your question is great, but I don't see that directly addressed in our course materials. Here's what the syllabus says about that topic..."

**Benefits for Student Learning:**
Students learn to navigate their actual course materials rather than relying on the LLM's general knowledge. This deepens engagement with assigned readings and course design.

**Benefits for Faculty Confidence:**
Faculty trust that Spark won't introduce incorrect information or bias from the broader internet. The assistant is constrained to what faculty have explicitly approved.

# 3.3 The Four-Week Rapid Implementation

Following the successful pilot, LAPU faced a decision: proceed cautiously with limited expansion or move to full implementation.

The data supported immediate action. The question became: How can we scale responsibly and quickly?

## 3.3.1 Conditions Enabling Rapid Scaling

**1. Faculty Buy-In Through Dialogue:** Months of informal conversations and open forums had already shifted faculty from skepticism to curiosity. Early adopters became champions who could model and mentor others.

**2. Leadership Clarity:** LAPU's Chief Academic Officer and senior leadership aligned around a vision: AI as a learning partner, not a threat. This clarity was essential for overcoming residual faculty concerns.

**3. Pedagogical Clarity:** The Socratic method provided a unifying approach that faculty could understand and teach. Instead of each course designing its own AI implementation, there was a clear pedagogical foundation.

**4. Technical Partnership:** Nectir's willingness to co-design and iterate rapidly was crucial. Rather than waiting for perfect product specifications, we worked in an agile, feedback-driven model.

**5. Scalable Content Alignment:** A structured prompt framework allowed Spark to be quickly trained on each course's content without extensive customization. Faculty could align Spark with their course in approximately 2-4 hours.

**6. Clear Communication:** A comprehensive communication plan prepared students, faculty, and staff for the rollout, with training videos, FAQs, and ongoing support.

## 3.3.2 The Rollout Timeline

- **Week 1:** Final faculty trainings; Spark integration into all LMS courses; student communication campaign begins
- **Week 2:** Faculty office hours and "Spark office hours" (time for faculty to experiment and ask questions)
- **Week 3:** Full availability; ongoing support and feedback collection
- **Week 4:** Analysis of early adoption data; iteration based on feedback

This accelerated timeline was possible because groundwork had been laid over months. It was not a thoughtless "move fast and break things" approach. Rather, it was informed by extensive preparation and ready to move quickly once conditions aligned.

# 3.4 Ethical Considerations and Ongoing Challenges

While our implementation has been largely successful, ethical challenges persist:

## 3.4.1 Data Privacy and Governance

**Challenge.** AI systems collect extensive student interaction data. How is this data stored? Who accesses it? Can students opt out?

**Our Approach.**

- All student data is stored on LAPU-controlled servers; Nectir does not retain copies
- Faculty cannot see individual student-Spark conversations (preserving psychological safety)
- Data governance policies comply with FERPA and protect student privacy
- Students are informed through privacy notices; however, genuine opt-out options are limited (since Spark is integrated into courses)

**Ongoing Work.** This remains an area requiring continuous attention. As AI systems become more sophisticated and data-intensive, institutions must proactively engage students in conversations about data use and ensure true informed consent.

## 3.4.2 Potential Biases in AI Responses

**Challenge.** Large language models are trained on internet data, which contains societal biases. Could Spark inadvertently reinforce stereotypes or provide biased information?

**Our Approach.**

- RAG constrains responses to course materials, reducing reliance on potentially biased general knowledge
- Spark's Socratic method prompts students to critically examine ideas rather than accept them as truth
- We've explicitly trained Spark not to make assumptions about student backgrounds or identity
- Ongoing monitoring and faculty feedback help identify and address problematic responses
- We've documented instances where Spark acknowledged uncertainty rather than confident falsehoods

**Ongoing Work:**
We need more robust auditing processes to systematically identify biases. This might include periodic testing with diverse student groups and external bias audits. We also recognize that even course materials can reflect institutional biases, so RAG alone doesn't eliminate the problem.

### 3.4.3 The Digital Divide

**Challenge.** Equitable access requires not just availability but digital literacy. Some students lack the technological fluency to use new tools effectively.

**Our Approach.**

- Embedded training videos teach students how to use Spark
- Faculty model Spark use in synchronous sessions and office hours
- Multiple access points (LMS, direct links) ensure accessibility
- Support staff provide one-on-one technical assistance

**Ongoing Work:**
Despite these efforts, students with lower digital literacy may experience barriers. We're developing more accessible onboarding experiences and exploring partnerships with student success coaching to reach digitally underconfident learners.

### 3.4.4 Maintaining Human Connection

**Challenge.** Might widespread use of AI reduce students' engagement with faculty and peers?

**Our Approach.**

- We've explicitly framed Spark as supplementary to—not a substitute for—instructor interaction
- Spark integrates into courses in ways that promote peer discussion, not replace it
- We've monitored instructor office hour utilization and discussion board engagement

**Data.** Students who use Spark at high levels do not show reduced instructor interaction. In fact, anecdotal evidence suggests that working through ideas with Spark sometimes prompts deeper questions to ask instructors.

**Ongoing Work:**
We need longitudinal data on whether Spark's presence affects the quality of student-faculty relationships and student sense of belonging to the learning community.

## 3.5 Faith-Informed Design

As a Christian-affiliated institution, LAPU integrated faith-informed considerations into AI implementation:

**Intentionality:** Technology should serve human flourishing, not replace human relationship. In our AI design, this meant ensuring Spark enhances rather than diminishes the educational relationship.

**Dignity:** Every person bears God's image. In Spark's design, this meant ensuring the tool respects student dignity by offering non-judgmental support and maintaining psychological safety.

**Justice:** Christian educational tradition emphasizes preferential option for the poor and vulnerable. We committed to ensuring AI benefits reached historically underserved students equitably.

**Wisdom:** Technology is powerful but limited. In our conversations about AI, we emphasized both enthusiasm for its potential and humility about its limitations.

These faith commitments were not separate from our technical decisions; they shaped them. For example, the Socratic method aligns with a view of education that honors student agency and capacity for growth—a deeply Christian educational philosophy.

---

# Part 4: Lessons Learned and Best Practices

## 4.1 Faculty Engagement is Non-Negotiable

**Finding:** Institutional success with AI depends primarily on faculty adoption and positive framing, not on technical sophistication.

**Best Practice:**

- **Start with dialogue, not mandates.** Create space for faculty to express concerns, questions, and ideas before deploying technology.
- **Identify early adopters.** Work with faculty already excited about pedagogy and innovation. Their enthusiasm becomes contagious.
- **Build faculty leadership.** Train faculty facilitators who can lead peer learning and model implementation.
- **Normalize experimentation.** Frame early months as "learning together," not as faculty implementing IT's vision.
- **Integrate into professional development.** Make AI literacy a regular part of faculty development, not a one-time training.

## 4.2 Communication and Marketing Matter

**Finding:** Lack of awareness and perceived necessity were primary barriers to adoption—not tool quality.

**Best Practice:**

- **Use multiple communication channels.** Email, LMS announcements, in-class demonstrations, videos, and peer testimonials all reinforce key messages.

- **Be specific about benefits.** Instead of "Spark can help with your studies," say "Spark can help you brainstorm essay topics, practice explaining key concepts, and get feedback on your writing—24/7."
- **Share student testimonials.** Peer voices are more persuasive than institutional messaging. Highlight diverse students—different majors, ages, backgrounds.
- **Demonstrate in context.** Show Spark in action, not in the abstract. Let students see real conversations and understand how to use it for their specific courses.
- **Follow the threshold.** Since three uses emerged as transformative, communication should encourage students to try Spark at least three times before deciding whether it's useful.

# 4.3 Integration Into Coursework is Key

**Finding:** Adoption is highest when Spark is integrated into assignments and active learning activities, not just available as an optional resource.

**Best Practice:**

- **Assign Spark-integrated activities.** "Before posting your initial discussion post, work with Spark on your main argument" integrates Spark naturally.
- **Use Spark in active learning.** Think-Pair-Share with Spark, role-plays, and simulations transform its role from optional support to core learning activity.
- **Make it easy.** Embed Spark directly in course materials, not as an external login. Reduce friction.
- **Model use.** Faculty should demonstrate Spark conversations in welcome videos, live sessions, and examples.
- **Reinforce metacognition.** Prompt students to reflect on their Spark conversations: "What did Spark's questions help you realize?"

# 4.4 Equity Requires Intentional Design

**Finding:** AI benefits are not automatically equitable. Benefits distribution depends on deliberate design choices.

**Best Practice:**

- **Assess your starting point.** Before implementation, measure baseline equity gaps in your institution.
- **Design for inclusion.** Make sure Spark is accessible to students with disabilities, ESL learners, and neurodivergent students. Test with diverse user groups.
- **Distribute benefits actively.** Don't assume students who need support most will find it. Use data to identify underutilizing students and provide targeted support.
- **Monitor outcomes by demographic group.** Regularly analyze data disaggregated by race, ethnicity, gender, and other dimensions. If you see disparities, investigate and adjust.
- **Listen to marginalized voices.** Create structured feedback mechanisms that specifically solicit input from students historically underserved by educational institutions.

## 4.5 Barriers are Solvable

**Finding:** Barriers to adoption are primarily informational and motivational, not technical.

**Best Practice:**

- **Diagnose your specific barriers.** Conduct surveys or focus groups to understand why students aren't using AI tools. Don't assume.
- **Tailor interventions.** If lack of awareness is the barrier, intensify communication. If perceived necessity is low, demonstrate value in specific contexts. If unfamiliarity is the issue, provide low-stakes opportunities to experiment.
- **Iterate based on data.** Collect regular feedback and make changes. Over time, adoption rates improve as word-of-mouth and experiences accumulate.

## 4.6 Ongoing Monitoring and Iteration are Essential

**Finding:** AI implementation is not a one-time event but an ongoing process of refinement.

**Best Practice:**

- **Establish baseline metrics.** Document GPA, course completion, engagement, and demographic outcomes before and after implementation.
- **Monitor leading indicators.** Track adoption rates, usage frequency, and satisfaction in real time, not just end-of-year reports.
- **Create feedback loops.** Regularly solicit input from students and faculty and visibly respond to it ("Based on your feedback, we've updated Spark to...").
- **Budget for improvement.** Allocate staff time and resources for ongoing development. The tool that launches is not the tool that will work best in year two.
- **Share results transparently.** Report outcomes regularly to stakeholders. Celebrate successes; acknowledge challenges and solutions candidly.

---

# Part 5: Scaling Responsibly—Global Implications

## 5.1 The Enrollment Crisis and AI's Role

Globally, higher education faces demographic headwinds. Birth rates in regions like the U.S. have fallen to 1.62 births per woman (2023), with K-12 enrollment projected to shrink by up to 20% in some areas over coming decades[5].

This poses an existential challenge: How do institutions maintain educational quality with fewer students and fewer resources?

AI is not a panacea, but it offers a crucial tool for **scalable, personalized support that human tutoring alone cannot provide**. As student populations shrink, AI can ensure that smaller cohorts of learners receive the individualized attention and immediate feedback that drive academic success.

This perspective reframes the AI debate: It's not about replacing teachers or cutting costs (though cost efficiency is a benefit). It's about sustaining educational quality and equity in a world with fewer human resources relative to student need.

## 5.2 Alignment with Sustainable Development Goal 4

The United Nations' Sustainable Development Goal 4 (SDG4) targets inclusive and equitable quality education. LAPU's AI implementation aligns with SDG4 in several ways:

**Ensuring Inclusive and Equitable Quality Education (SDG 4.1)**
By providing AI assistance equitably across demographic groups, LAPU ensures that quality support reaches all students, not just those with access to expensive tutoring.

**Promoting Lifelong Learning (SDG 4.3)**
AI assistants support diverse learners—adult professionals, parents, students with disabilities—who might not fit traditional educational molds. This democratizes access to learning opportunities.

**Building Inclusive Learning Environments (SDG 4.a)**
Spark's accessibility features (language adaptation, non-judgmental support, 24/7 availability) create inclusive learning environments for students who experience barriers in traditional educational contexts.

**Supporting Equitable Teacher Development (SDG 4.c)**
Rather than asking teachers to do more with less, AI supplements teacher capacity, allowing educators to focus on higher-order teaching—relationship-building, feedback, and mentorship—rather than routine content delivery.

## 5.3 Responsible AI Implementation Framework

Based on our experience, institutions seeking to implement AI responsibly should consider this framework:

**Phase 1: Readiness and Alignment (2-3 months)**

- Assess institutional readiness: Do you have faculty willing to experiment? Clear pedagogical values? Commitment to equity?
- Engage stakeholders in dialogue: What are faculty concerns? What does the student population need?
- Clarify institutional values: What does student-centered learning mean at your institution? How does AI align with or challenge that vision?

**Phase 2: Design and Pilot (3-4 months)**

- Select a pedagogical approach aligned with your values (e.g., Socratic method for critical thinking)
- Partner with a vendor or develop tools aligned with your approach
- Conduct a small-scale pilot with rigorous evaluation (RCT if possible)
- Collect qualitative feedback from early users

**Phase 3: Expansion with Iteration (6-12 months)**

- If pilot results are positive, expand cautiously—not to all courses at once, but in waves
- Identify early adopters to serve as faculty leaders
- Systematically integrate AI into courses and active learning activities
- Monitor outcomes by demographic group; adjust as needed

**Phase 4: Mainstreaming and Sustainability (12+ months)**

- Integrate AI into standard institutional practices (faculty development, curriculum design, student support)
- Develop scalable support structures (faculty facilitators, peer tutors trained in AI)
- Establish governance: How will institutional AI decisions be made? Who approves new uses?
- Build in regular evaluation: What are we learning? What needs to change?

Throughout this process, maintain unwavering attention to:

- **Pedagogy first:** Technology should serve your educational mission, not drive it
- **Equity second:** Continuously ask: Are benefits reaching all students? Are any groups being left behind?
- **Ethics third:** What data are you collecting? Who has access? What safeguards exist?
- **Humanity last (but always):** How does this maintain human connection and agency?

---

# Part 6: Limitations and Future Research

## 6.1 Study Limitations

While our research provides valuable insights, several limitations merit acknowledgment:

**Sample Size and Generalizability[2]**
While the quasi-experimental study involved 2,090 student-course combinations across 99 courses, the research was conducted at a single institution. LAPU is a fully online, faith-based, adult-serving university. Findings may not generalize to traditional residential institutions, institutions serving primarily traditional-age students, or institutions with different institutional missions.

**Measurement of Surrogate Outcomes[1]**
We used GPA as a primary outcome measure, acknowledging that grades are a proxy for learning, not learning itself. Deeper measures of conceptual understanding, transfer of learning, and long-term retention would strengthen our evidence base.

**Selection Bias[1]**
Students self-selected into treatment and control groups based on their choice to use Spark. While we controlled for confounding variables through propensity score matching and permutation analysis, unmeasured variables (e.g., baseline academic motivation, technology comfort) may have influenced outcomes.

**Social Desirability Bias in Survey Responses[2]**
Students' self-reported feelings of engagement and support may have been influenced by awareness that they were using a novel, institutional tool. Positive responses may partly reflect enthusiasm for novelty rather than genuine improvements in experience.

**Limited Longitudinal Data**
Our data span two years of implementation, but longer-term follow-up is needed to understand sustained effects. Do benefits persist after the novelty wears off? What is the long-term effect on student retention and degree completion?

# 6.2 Future Research Directions

Several important research questions remain:

**1. Long-Term Learning Outcomes**
Does usage of AI assistants affect student retention, degree completion, and post-graduation success? Do learning gains persist beyond the semester or course in which Spark was used?

**2. Interaction with Other Support Systems**
How do AI assistants interact with existing human support (faculty feedback, tutoring, success coaching)? Is there a synergistic effect, or do they substitute for human support?

**3. Different AI Approaches and Designs**
Our research focused on one specific approach (Socratic method, RAG-constrained, course-specific). How do outcomes differ with other design choices? What is the relative importance of different design features?

**4. Qualitative Understanding of Student Experience**
While we have quantitative data on outcomes, deeper qualitative research exploring how students experience AI-mediated learning would enrich understanding. How do students perceive the relationship with an AI assistant? Does it affect their sense of belonging or identity as a learner?

**5. Faculty Experience and Pedagogy**
How does integrating AI change faculty pedagogy? Does it alter the instructor role? How do faculty experience this change? Are there differential effects for faculty at different career stages or with different teaching philosophies?

**6. Equity Beyond Demographic Categories**
While we found no disparities across race, ethnicity, gender, and age, other dimensions of equity matter: first-generation status, disability status, parental status, socioeconomic status. Does AI benefit reach these groups equitably?

**7. Scaling to Diverse Institutional Contexts**
How do findings generalize to traditional residential institutions, teaching-focused universities, research universities, community colleges, and international contexts? What adaptations are needed for different institutional types?

**8. Ethical and Governance Implications**
As AI becomes more autonomous and data-intensive, how should institutions govern AI use? What ethical frameworks guide responsible deployment? How do we ensure student consent is genuine and informed?

---

# Conclusion: What Two Years of Full AI Integration Has Taught Us

Over two years, LAPU has moved from asking "Should we use AI?" to asking "How can we use AI most effectively, ethically, and equitably?" This shift reflects a maturation of our institutional thinking.

## What We Know

The evidence is clear: **When AI is intentionally designed, embedded in sound pedagogy, and implemented with attention to equity, it significantly improves student academic performance, motivation, and sense of belonging—without widening existing disparities.**

- Students who engaged with Spark achieved 0.28 GPA points higher than non-users (a meaningful difference in online higher education)
- Benefits were equitably distributed across demographic groups
- The barriers to adoption were informational and motivational, not technical—solvable through better communication and integration
- Faculty partnership and positive framing were more important than technical sophistication
- Belonging is complex; AI's role is not to create belonging alone but to support it as part of a larger ecosystem

## What We Don't Yet Know

Important questions remain: Will benefits persist over time? How does AI interact with different institutional contexts, teaching philosophies, and student populations? How should we govern AI responsibly as these systems become more powerful?

## What We Believe

Based on our experience, we believe:

1. **AI is not a threat to higher education; uninformed, inequitable implementation is.** The question is not whether to use AI but how to use it in ways aligned with institutional values and serving all students equitably.

2. **Faculty and pedagogy must lead; technology follows.** Successful AI implementation begins not with technology selection but with clarity about what we value in learning and teaching.

3. **Equity requires intentional design and ongoing monitoring.** Benefits do not automatically reach underserved populations. Institutions must proactively ensure that AI serves all students.

4. **Belonging matters as much as academic performance.** The most powerful finding from our research is that AI can foster a greater sense of belonging for students initially feeling disconnected. This is perhaps more important than any GPA gain.

5. **Humans remain essential.** AI amplifies human capability; it does not replace it. The future of higher education is not AI or human educators—it's both, working in partnership for student learning.

## A Final Word: The Human in Human-Centered Learning

As we celebrate AI's potential in education, we must never lose sight of what education fundamentally is: an encounter between human beings—teacher and learner—in pursuit of truth, growth, and flourishing.

Technology should serve this encounter, not replace it. At LAPU, Spark is present in every course, but so is a professor who cares about students' learning. Students access AI support 24/7, but they also have a success coach who knows their name and calls them by it. We've embraced innovation, but we've never lost sight of our founding mission: educating the whole person in a community of learning.

This is the model we offer to the field. It is rigorous in its commitment to evidence and outcomes. It is bold in its embrace of emerging technology. And it is humble in its recognition that technology, for all its power, serves human learning and human connection.

## Path Forward for LAPU

As we look to the next phase of our work, we are committed to:

1. **Continuing rigorous research** to understand long-term effects and optimal implementation
2. **Expanding access** to AI support in competency-based programs and specialized educational formats
3. **Deepening integration** of AI into active learning and high-impact practices
4. **Addressing remaining barriers** to adoption through improved communication and faculty development
5. **Maintaining ethical vigilance** around data privacy, potential biases, and responsible governance
6. **Sharing our learning** with peers through publications, conferences, and collaborative research networks

We believe higher education stands at an inflection point. The institutions that will thrive in coming decades are those that harness emerging technology thoughtfully, equitably, and ethically—while maintaining unwavering commitment to human-centered learning and student success.

LAPU's journey with AI is just beginning. We invite other institutions to learn from our experience—to adapt what works, question what doesn't, and build together toward a future of higher education that is both innovative and humane.

---

# References

[1] Hanshaw, G., Wicker, E., & Denlinger, K. (2025). An experimental study of the effect of AI course assistants on student grade outcomes. *Open Praxis*, 17(2), 270–285. https://doi.org/10.55982/openpraxis.17.2.772

[2] Hanshaw, G., Vance, J., & Brewer, C. (2024). Exploring the effectiveness of AI course assistants on the student learning experience. *Open Praxis*, 16(4), 627–644. https://doi.org/10.55982/openpraxis.16.4.719

[3] Hanshaw, G., & Sullivan, C. (2025). Exploring barriers to AI course assistant adoption: A mixed-methods study on student non-utilization. *Discover Artificial Intelligence*, 5(178). https://doi.org/10.1007/s44163-025-00312-x

[4] Ho, Y., Hanshaw, G., Wilday, M., & Dawson, C. (2024). AI is part of the belonging ecosystem. In *University of Arizona Global Campus 2024 Teaching and Learning Conference Proceedings*.

[5] Hanshaw, G. (2024). Equity by design: Implementing AI course assistants to support student success in online higher education. In *Artificial Intelligence in Education: Creating an Equitable, Creative, and Effective Learning Environment*. IntechOpen. https://doi.org/10.5772/intechopen.1012800

[6] Hanshaw, G., & Wilday, M. (2025). Implementing AI course assistants: A rapid design case from concept to full rollout at Los Angeles Pacific University. *International Journal of Designs for Learning*, 16(2), 222–235. https://doi.org/10.14434/ijdl.v16i2.41926

---

# Appendices

## Appendix A: Sample Student Testimonials

*"Talking to Spark gave me the courage to share my real opinion. By the time I posted, I knew I had already tested my idea in a safe space."*

*"Spark doesn't do the work for you. Spark asks me questions on what I already know and it was like Spark and I did the work together."*

*"I used Spark when I did not understand what I was reading. And when Spark explained the difficult concept for me, I finally understood."*

*"Thanks for modeling for us how to use Spark. I think Spark is cool. I can ask Spark questions even at 3 AM in the morning. I learned a lot about how to outline a paper from Spark."*

*"Spark does not write the essay for the student. Instead, Spark encourages students to write the essay themselves because of the probing critical thinking questions it provides."*

---

**Institutional Evidence Report Prepared By:**
George Hanshaw, Psy.D., Director of Digital Learning Solutions, Los Angeles Pacific University

Craig Brewer, Ed.D., Assistant Dean, Los Angeles Pacific University

Shannon Hunt, Professor, Los Angeles Pacific University

Bachelors of Applied Psychology | Masters of Applied Psychology | Criminal Justice

**January 2026**