ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

2026 REFEREED PROCEEDINGS

FEDERATION OF BUSINESS DISCIPLINES

March 2026
Richardson, Texas

ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

2026 Refereed Proceedings

Richardson, Texas

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ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

CONGRATULATIONS!

Recipient of the ABIS 2026 Federation of Business Disciplines

Distinguished Paper Award

AI Student Perspectives – Exploring how Students in College of Business Classes are Using AI Inside and Outside the Classroom

Lori Soule, Nicholls State University
Sherry Rodrigue, Nicholls State University
Betty Kleen, Nicholls State University

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Association of Business Information Systems

ABIS 2026 Program Overview

Wednesday, March 18, 2026

1:30 p.m. – 3:00 p.m.	Session A: **ABC-SWUS & ABIS Joint Session –** **Beyond the Algorithm: Humanity and the Hybrid Workplace**
3:30 p.m. – 5:00 p.m.	Session B: **ABC-SWUS & ABIS Joint Session –** **Building Digital Pathways: From Classroom Innovation to Career Readiness**
6:30 p.m. – 7:30 p.m.	**FBD Awards & Recognition Reception**
7:30 p.m. – 9:30 p.m.	**FBD Awards & Recognition Dinner**

Thursday, March 19, 2026

7:30 a.m. – 8:30 a.m.	**ABIS & ABC-SWUS Joint Breakfast**
8:30 a.m. – 10:00 a.m.	Session C: **ABC-SWUS & ABIS Joint Session –** **Distinguished Paper Presentations**
10:30 a.m. – 11:45 a.m.	Session D: **Inside the Student-AI Experience**
11:45 a.m. – 1:30 p.m.	**Lunch on your own** ***Executive Board Meeting (by Invitation)**
1:30 p.m. – 3:00 p.m.	Session E: **Brains, Bots, and Business: Teaching with AI**
3:30 p.m. – 5:00 p.m.	Session F: **Decoding the Digital World**
5:30 p.m. – 7:00 p.m.	**FBD Presidential Welcome Reception**

Friday, March 20, 2026

7:30 a.m. – 8:30 a.m.	**ABIS & ABC-SWUS Joint Breakfast**
8:30 a.m. – 10:30 a.m.	Session G: **ABIS Business Meeting *All Members Welcome***
11:00 a.m. – 12:00 p.m.	Session H: **Keynote Panel: The Convergence Agenda: Bridging the Academy-Industry Digital Divide**
12:00 p.m. – 1:30 p.m.	**Lunch on your own**
1:30 p.m. – 3:00 p.m.	Session I: **Bridging the Digital Divide in Higher Ed**
3:30 p.m. - 5:00 p.m.	Session J: **Intelligent Enterprises: How AI Is Redefining Business**

ASSOCIATION OF BUSINESS INFORMATION SYSTEMS

March 18, 2026
(Wednesday)

1:30 p.m. – 3:00 p.m.	Wildflower 3

SESSION A **ABC-SWUS and ABIS Joint Session: Beyond the Algorithm: Humanity and the Hybrid Workplace**

Moderator: **Lindsay Clark**, Sam Houston State University

The (In)Humanness of AI Chatbots in the Classroom
Ashly Smith, Sam Houston State University
Lindsay Clark, Sam Houston State University

Why Hire a Human? Teaching Students to Articulate Value in AI-Integrated Workplaces
Timothy Ponce, Texas State University

Build Your Own AI Class Agent: It's Not Rocket Science
Dejan Terzic, The University of Texas at Arlington
Heather Philip, The University of Texas at Arlington
Kevin Carr, The University of Texas at Arlington

ROI Case for IBM's AI-Driven HR Tool
Vianka Miranda, Northwestern State University of Louisiana
Elizabeth Prejean, Northwestern State University of Louisiana
Douglas Moran, Northwestern State University of Louisiana

3:00 p.m. – 3:30 p.m.	Wildflower 3

ABCSW & ABIS - Joint Session-Networking and Coffee Break

3:30 p.m. – 5:00 p.m.	Wildflower 3

SESSION B **ABC-SWUS and ABIS Joint Session -- Building Digital Pathways: From Classroom Innovation to Career Readiness**

Moderators: **Timothy Ponce,** Texas State University
Shane Schartz, Fort Hays State University

Using AI for Qualitative Research: An Exploratory Study
Carol Wright, Stephen F. Austin State University
Kayla Sapkota, Arkansas State University at Beebe

Toward a Self-Learning Institutional Framework for Student Retention and Success
Nabin Sapkota, Northwestern State University of Louisiana
Mary Fair, Northwestern State University of Louisiana
Damien Tristant, Northwestern State University of Louisiana
Marcia Hardy, Northwestern State University of Louisiana

The College Handshake Job Information System: Teaching College Students How to Utilize It for Career Opportunities
Marice Kelly, Stephen F. Austin State University
Karina Tergerson, Stephen F. Austin State University

3:30 p.m. – 5:00 p.m. – continued | Wildflower 3

The Path to CPA Licensure: Evolving Requirements and the Future of the Profession
Melissa Aldredge, Northwestern State University of Louisiana
Haeven Durbin, Northwestern State University of Louisiana
Vianka Miranda, Northwestern State University of Louisiana

CONGRATULATIONS!

Recipient of the 2026 FBD Outstanding Educator Award

Mahesh S. Raisinghani

Texas Women's University

March 19, 2026
(Thursday)

7:30 a.m. – 8:30 a.m.	Texas 5

ABC–SWUS and ABIS Joint Breakfast

We invite ABC-SWUS and ABIS Associations presenters and members to enjoy breakfast together!

ABC-SWUS or ABIS Association Name Badge Required for Entry

8:30 a.m. – 10:00 a.m.	Joint Session with ABC-SWUS	Texas 5

SESSION C **ABC-SWUS and ABIS Joint 2026 Distinguished Paper Session**

Session Chairs: **Kristen Wilson**, Eastern Kentucky University
Jason Powell, Northwestern State University of Louisiana

ABC-SWUS Distinguished Paper: *Transforming Business Communication: The Integration of Artificial Intelligence into the Curriculum*
Marcel Robles, Eastern Kentucky University

ABIS Distinguished Paper: *AI Student Perspectives – Exploring how Students in College of Business Classes are Using AI Inside and Outside the Classroom*
Lori Soule, Nicholls State University
Sherry Rodrigue, Nicholls State University
Betty Kleen, Nicholls State University

10:00 a.m. – 10:30 a.m.	Foyer

FBD Coffee Break

Please attend the poster sessions and visit the exhibits for information on the latest books and newest educational technologies. Let our exhibitors know how much we appreciate their continued support!

10:30 a.m. – 11:45 a.m.	Spring Creek

SESSION D **Inside the Student-AI Experience**

Session Chair: **Sherry Rodrigue,** Nicholls State University

Student Usage of AI: A Preliminary Survey Results
Carla Barber, University of Central Arkansas
Michael Ellis, University of Central Arkansas

Panel: Beyond the Hype: Student Voices on Artificial Intelligence in Education
Jason Powell, Northwestern State University of Louisiana
Weiwen Liao, Northwestern State University of Louisiana
Joseph Adams, Tyler Junior College
Justin Dysarz, Northwestern State University of Louisiana
Dexteria King, Northwestern State University of Louisiana

March 19, 2026
(Thursday)

11:45 a.m. – 1:15 p.m.	**Lunch on your own**

ABIS Executive Board Meeting and Luncheon by Invitation Only (Location: Richardson Boardroom)

1:30 p.m. – 3:00 p.m.	Spring Creek

SESSION E **Brains, Bots, and Business: Teaching with AI**

Session Chair: **Robert Wright**, Texas State University

Artificial Intelligence in Teaching Business: Opportunities, Challenges, and Pedagogical Responses
Marcel Robles, Eastern New Mexico University

Responsible AI Integration in Business Information Systems: Balancing Efficiency and Ethics
Sayed Muhammad Sajid Zia Zanjani, Australian Institute of Higher Education, Australia
Azmat Ullah, Australian Institute of Higher Education, Australia
Hassan Ali Raza, Beijing Institute of Technology, China
Muhammad Nabeel Raza, Science Island Branch Graduate School University of Science and Technology Hefe, Anhui, China
Syed Muhammad Wasil Mustanir, BPP University Portsoken Campus London, United Kingdom

When to AI: Comparing Perceptions of Appropriate Use
Kerianne Roper, Oklahoma Christian University
Marianna Bayona Oklahoma Christian University
Sophie Bennett, Oklahoma Christian University
Olivia Jackson, Oklahoma Christian University
Jan Jewett, Oklahoma Christian University
Kimberly Merritt, Oklahoma Christian University

Bridging the AI Literacy Gap: Developing Ethical and Effective AI Education
Doug Darby, Lubbock Christian University
Dana Harris, Lubbock Christian University

3:00 p.m. – 3:30 p.m.	Exhibit Hall

FBD Coffee Break

Please attend the poster sessions and visit the exhibits for information on the latest books and newest educational technologies. Let our exhibitors know how much we appreciate their continued support!

3:30 p.m. – 5:00 p.m.	Spring Creek

SESSION F **Decoding the Digital World**

Session Chair: **Carla Barber,** University of Central Arkansas

Cloud-Based Data Management: Challenges, Solutions, and Future Directions
Mahesh Raisinghani, Texas Women's University
Atieno Amadi, Texas Women's University
Y Nguyen, Texas Women's University
Omolola James, Texas Women's University
Jennifer Kiefling Brown, Texas Women's University

March 19, 2026
(Thursday)

3:30 p.m. – 5:00 p.m. – continued	Spring Creek

The Secret Life of Emojis: Smuggling Subtext in Education and Justice
Daniel Gordy, Northwestern State University of Louisiana

Universal New Interoperable Control Blockchain Protocol (UNIC-BP)
Ray Aria, University of Houston Downtown
Jinho Kim, University of Houston Downtown

The Digital Divide: Technology as a Site of Contention in the Remote Work Era
Atieno Amadi, Texas Women's University
Mahesh Raisinghani, Texas Women's University

5:30 p.m. – 7:00 p.m.	Foyer

FBD Presidential Welcome Reception

All registered participants and paid guests are invited to the FBD President's Reception in the Exhibit Hall to network with colleagues and exhibitors while enjoying drinks and appetizers. Alcoholic drinks will be available through drink tickets or cash bar. **All attendees must be wearing the FBD badge received at registration to enter the reception. Name badges must be picked up before 4:30 pm on Thursday, March 19.**

Enjoy your evening in Richardson!

March 20, 2026
(Friday)

7:30 a.m. – 8:30 a.m.	Texas 5

ABCSW & ABIS-Breakfast

We invite ABC-SWUS and ABIS Associations presenters and members to enjoy breakfast together!

ABC-SWUS or ABIS Association Name Badge Required for Entry

8:30 a.m. – 10:00 a.m.	Spring Creek

SESSION G **ABIS Business Meeting** *** All Members Welcome ***

Moderators: **Mahesh Raisinghani**, Texas Women's University
Jason Powell, Northwestern State University of Louisiana

All members are invited to join us for our annual business meeting.

10:00 a.m. – 10:30 a.m.	Foyer

FBD Coffee Break

Please attend the poster sessions and visit the exhibits for information on the latest books and newest educational technologies. Let our exhibitors know how much we appreciate their continued support!

11:00 a.m. – 12:00 p.m.	Spring Creek

SESSION H **Keynote Panel: The Convergence Agenda: Bridging the Academy-Industry Digital Divide**

Speakers: **Michael S. Raisinghani,** Texas Women's University
Atieno Amadi, Texas Women's University
Gaurav Shekhar, The University of Texas at Dallas
Sam Rufus, Deloitte University

12:00 p.m. – 1:30 p.m.	**Lunch on you own**

Enjoy local cuisine in Richardson!

1:30 p.m. – 3:00 p.m.	Spring Creek

SESSION I **Bridging the Digital Divide in Higher Ed**

Session Chair: **Robert Wright,** Texas State University

Digital Disconnect: Investigating Faculty Competence, Morale, and the Assumptions of a Digital Master Plan
Shane Schartz, Fort Hays State University

A Quest for Analytics: The Trials and Tribulations of Implementing a Data Analytics Program
Shane Schartz, Fort Hays State University

Just What is the Measure of Success? A Pluralistic Stakeholder Centric Study of System Implementation Success in Academic Information Systems
Joseph Mansour, University of Louisiana Monroe

From Automation to Innovation: AI and ML in Business Information System Transformation
Azmat Ullah, Australian Institute of Higher Education, Australia
Sayed Muhammad Sajid Zia Zanjani, Australian Institute of Higher Education, Australia
Hassan Ali Raza, Beijing institute of Technology China
Muhammad Nabeel Raza, Science Island Branch Graduate School University of Science and Technology Hefe, Anhui, China
Syed Muhammad Wasil Mustanir, BPP University Portsoken Campus London, United Kingdom

3:00 p.m. - 3:30 p.m.	Foyer

FBC Coffee Break

Please attend the poster sessions and visit the exhibits for information on the latest books and newest educational technologies. Let our exhibitors know how much we appreciate their continued support!

3:30 p.m. - 5:00 p.m.	Spring Creek

SESSION J **Intelligent Enterprises: How AI Is Redefining Business**

Session Chair: **Jason Powell,** Northwestern State University of Louisiana

How AI Influences Learning Theories in the Consumer Decision-Making Process
Connie Clary, Lubbock Christian University
Dana Harris, Lubbock Christian University

AI Transformation in Enterprises: A General Roadmap and Balanced Evaluation Framework
Xiangjie Qu, Pittsburg State University
Larry Woodward, Pittsburg State University

A Panel Discussion on Dark Factories, Risk Management, and Engineering Technology in Computer Information Systems
Carmella Parker, Northwestern State University of Louisiana
Mary Fair, Northwestern State University of Louisiana
Nabin Sapkota, Northwestern State University of Louisiana
Valerie Salter, Northwestern State University of Louisiana
Marcia Hardy, Louisiana Christian University

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Please make plans to join us next year for our 2027 conference.

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AI STUDENT PERSPECTIVES – EXPLORING HOW STUDENTS IN COLLEGE OF BUSINESS CLASSES ARE USING AI INSIDE AND OUTSIDE THE CLASSROOM

Lori Soule, Nicholls State University
Sherry Rodrigue, Nicholls State University
Betty Kleen, Nicholls State University

ABSTRACT

This study extends prior research on Artificial Intelligence (AI) in higher education by presenting the results of a survey administered to students enrolled in business classes at a mid-sized public university in the southern United States. Building on a previous literature review of student use and perceptions of AI, this paper incorporates additional literature and analyzes student responses regarding their usage and attitudes toward AI tools in academic, personal, and professional contexts. Findings reveal AI software is highly adopted by students in various academic and personal settings, but usage and perceptions do differ based on variables such as gender, age, and major. The study contributes to the growing body of research on AI integration in higher education. These results will contribute to future research, including planned faculty surveys, and support ongoing discussions on how business programs can prepare students for careers in an AI-driven environment.

Keywords: Artificial Intelligence, AI, Generative AI, Higher Education, Student Use of AI

INTRODUCTION

Nearly three years after its introduction, ChatGPT is still referred to as "*one of the most popular internet apps ever*" (Heaven, 2023). However, even with such a large adoption and utilization rate, many individuals and organizations seek to find and define the best approach to incorporating such a tool into their personal and professional lives. Similarly, those aligned in all areas of higher education also seek to find a balance regarding artificial intelligence (AI) in the classroom and students' expected knowledge of AI tools upon graduation.

Artificial Intelligence in Education (AIED) research is limited and has varied views, particularly regarding some of the large language models and generative AI applications such as ChatGPT. As the models and capabilities continue to evolve at rapid speeds, some of the initial AI views and policies have also quickly evolved. Many colleges and universities initially prohibited the use of AI, asserting that any use of AI is considered cheating or plagiarism. However, with the business community embracing AI tools to help increase productivity and minimize repetitive and time-consuming tasks, universities realize that they must provide graduates with AI experience. A 2023 exploratory study by Cardon et al. agreed that business students must develop AI literacy to succeed in the workplace (Cardon, Fleischmann, Aritz, Logemann, & Heidewald, 2023).

A July 2025 research report by SHRM, Society for Human Resource Management, shows that nearly 45% of U.S. workers reported using AI tools in their jobs. However, adoption rates varied greatly across generations, genders, and industries. Millennial AI usage led the age groups with 56% utilization of AI tools, while Baby Boomers only reported 25% utilization. Of those using

AI, 77% stated that it helped them accomplish more in less time, and 73% stated that AI tools improved their quality of work. Fifty-one percent of workers agreed that AI training should be a top priority for companies, emphasizing the importance of upskilling and reskilling current workers to harness AI's potential (SHRM, 2025).

The question is not <u>if</u> college students should have access to AI tools in their college classrooms, but <u>how</u> college courses and universities can best incorporate AI into their graduates' list of competencies and skillsets. In particular, how are colleges of business preparing their graduates with the AI knowledge that businesses are expecting?

The purpose of this paper is to present the findings of a recent study of 416 students enrolled in business classes at a mid-sized public university in the southern United States. The study was designed to determine which of the available AI software students were using in different settings. In addition, the students' feelings toward using AI in personal, academic/school, and work situations were assessed. The authors intend to use this study to help faculty learn how their students are currently using AI and their perceptions of it. The authors also plan to further this study with future research on faculty usage and perception of AI in personal and professional settings.

REVIEW OF THE LITERATURE

Generative artificial intelligence (GenAI) refers to a category of AI models designed to create new content, such as text, images, audio, or code, by learning patterns from existing data. These models, including large language models (LLMs) like ChatGPT, generate outputs that are not merely retrieved or classified but are novel and contextually relevant based on user prompts. This distinguishes generative AI from traditional AI systems, which typically perform predictive or analytical tasks such as classification, recommendation, or decision-making based on structured inputs. Generative AI expands the scope of AI from automation and optimization to creative and cognitive augmentation, enabling new forms of interaction and productivity (IBM Research, 2023).

While students are rapidly integrating AI into their academic workflows, often for writing assistance, summarization, and research support, many colleges and universities are struggling to keep up. Recent research from the Graduate Management Admission Council (GMAC) highlights the evolving landscape of generative AI in higher education, revealing both promising trends and significant institutional challenges (GMAC, 2025). According to the report, student adoption of GenAI tools is outpacing institutional readiness. The data shows that only a small fraction of institutions have implemented comprehensive AI strategies, and even fewer have developed clear policies or support systems to guide ethical and effective use.

Among the report's key findings, three stand out (GMAC, 2025). First, there is a notable gap between ambition and execution. Higher education institutions express a strong interest in leveraging GenAI but lack the infrastructure and expertise to deliver on that ambition. Next, student adoption is leading the way, with learners experimenting with GenAI tools independently, often without formal guidance or oversight. Third, barriers to institutional adoption include limited resources, insufficient training for faculty and staff, and a lack of confidence in the ethical, academic integrity, and data privacy implications of GenAI. These concerns are compounded by the absence of standardized rules or policies about the approved use of AI, leaving many institutions vulnerable to misuse or inequitable access.

The GMAC 2025 report also identifies future developments that could help bridge this gap. One promising trend is the emergence of education-specific enterprise licenses for GenAI platforms. These licenses are designed to offer tailored features for academic environments, including enhanced privacy protections, content moderation, and integration with learning management systems. Such developments may enable institutions to better align GenAI tools with pedagogical goals while maintaining ethical standards and safeguarding student data (GMAC 2025).

The slower adaptation rate of higher education institutions, coupled with the swift progress of AI tools and models, leads one to wonder if institutions will ever catch up with this ever-changing environment. Not only are the AI tools rapidly evolving, but the ways and frequency with which students are interacting with the tools are also rapidly changing. Even faculty who have embraced AI and changing technology are having trouble adapting. Recent survey data from Rollins College in Florida offers a similar view of how students are engaging with AI tools in their academic work. Among 119 respondents, nearly 72% reported using AI at least once per week, with 15% indicating daily use (The Sandspur, 2025). This suggests a growing normalization of AI-assisted learning among college students. The most common academic tasks for which students sought AI assistance included summarizing readings (48%), grammar and translation support (45%), and research or source discovery (32%). These findings reflect a shift in how students approach traditional academic tasks, leveraging AI to streamline and enhance their learning processes.

Despite this widespread use, faculty encouragement of AI remains inconsistent. As reported in the Rollins College study, only 6% of students reported that their professors “very often” encouraged AI use, while 22% said it was “rarely” encouraged and 11% said “never” (The Sandspur, 2025). This gap between student adoption and faculty endorsement may reflect broader concerns about the ethical implications of AI in education. While the survey did not directly measure concern levels, the uneven faculty support and reliance on AI for core academic tasks suggest a tension between innovation and integrity. As AI tools become more embedded in higher education, institutions may need to develop clearer guidelines and pedagogical strategies to address both the opportunities and challenges they present.

A 2025 report from the Association to Advance Collegiate Schools of Business (AACSB) highlights a growing divide between business school deans and faculty regarding the adoption of AI in higher education (Leckrone, 2025). While both groups generally agree that students and instructors are embracing generative AI tools, their views diverge on institutional support and implementation. According to the report, 85% of deans said their schools encourage faculty to integrate AI into the curriculum, compared to only 63% of faculty who felt similarly supported. This gap extends to other areas such as using AI for teaching, curriculum development, and administrative tasks. Despite these differences, 65% of deans plan to integrate AI into existing courses within the next year, and 37% intend to allocate funding for AI-focused initiatives, including innovation labs and partnerships with tech companies.

These findings (Leckrone, 2025) suggest that while enthusiasm for AI is strong among leadership, faculty adoption may lag due to limited institutional guidance or differing pedagogical priorities. The AACSB report underscores the need for clearer policies and collaborative strategies to ensure that AI integration aligns with both instructional goals and ethical standards in business education.

In a recent article in Forbes, Dr. Aviva Legatt (2025) also highlights a disconnect between student adoption and institutional readiness. While students are integrating AI into their academic routines independently, many institutions lack formal policies or curricular support. This gap has led to frustration among students who seek clearer guidance and ethical frameworks. In the article, a 2025 AI in Education Trend Report by Copyleaks was discussed. That survey of over 1,100 U.S. students revealed that 90% have used AI academically across two-year colleges, four-year universities, and graduate programs, thus showing that the widespread adoption of generative AI among college students has accelerated rapidly. Notably, the largest share of users were adult learners aged 45 - 60, indicating that AI use extends beyond traditional undergraduate populations. Students reported using AI for brainstorming, drafting, outlining, and clarifying complex concepts, with motivations centered on improving work quality, saving time, and enhancing understanding. Legatt argues that higher education must prioritize AI fluency, not just technical skills, but also ethical and strategic understanding, to prepare students for a workforce increasingly shaped by AI technologies.

As AI becomes increasingly integrated into higher education, educators face the challenge of guiding students toward ethical use rather than focusing solely on misconduct. Zakrajsek (2025) argues that the emphasis should shift from punitive measures to proactive strategies that foster integrity and transparency. Drawing on decades of research into academic dishonesty, the article identifies key factors that contribute to misconduct, such as peer normalization, pressure to succeed, and perceptions of meaningless assignments, and suggests that these same factors may influence inappropriate AI use.

To address these concerns, Zakrajsek (2025) proposes four strategies: (1) designing assignments that reduce opportunities for misconduct, such as requiring drafts or in-class work; (2) setting clear expectations for acceptable AI use, including specific examples of permitted and prohibited actions; (3) requiring AI disclosure statements in student submissions to promote transparency; and (4) discussing honor and integrity openly while using AI detection tools cautiously due to their limitations and potential bias against non-native speakers and neurodivergent learners. These strategies aim to create a classroom culture that supports ethical decision-making and responsible AI use, rather than relying solely on surveillance and punishment.

Understanding how and why students are using AI tools may also help faculty determine how to incorporate those tools and skills into their curriculum. A recent survey conducted at Middlebury College in Vermont sheds light on the various ways students are incorporating generative AI into their academic work. According to Reyes (2025), over 80% of students reported using AI tools, such as ChatGPT, to support their coursework. Interestingly, the majority of students (61%) used AI for augmentation, tasks like summarizing readings, proofreading, and clarifying concepts, rather than automation, such as generating essays or solving assignments. This distinction suggests that students are leveraging AI as a learning aid rather than a shortcut, often describing it as an “on-demand tutor” that supplements traditional academic support.

The same survey (Reyes, 2025) also revealed that students tend to use AI more frequently during high-pressure periods, such as exam weeks, and for low-stakes assignments. While concerns about academic integrity persist, these findings challenge the assumption that AI use inherently undermines learning. Instead, they point to a growing trend of thoughtful integration, where students use AI to enhance their understanding and productivity. This underscores the importance of developing institutional policies that guide ethical and effective AI use in higher education.

Understanding when students are most likely to use AI tools, what tools they are using, and how they are using those tools may help faculty find ways to integrate AI into their courses and curriculum, as well as feel more comfortable with allowing students to incorporate AI as part of their work. For colleges of Business, understanding what AI skills and experience employers are expecting graduates to have may help them find realistic and practical applications of AI that enhance the learning experience and prepare students for their future careers.

RESEARCH METHODOLOGY

During the summer of 2025, the authors designed a survey to be administered to students enrolled in courses hosted by the College of Business Administration. The students attend a mid-sized public university in the southern United States. The University's Human Subjects Institutional Review Board reviewed the study plan and survey design and granted approval to proceed with the dissemination of the survey. In early Fall 2025, faculty received an email link to the survey created in Google Forms for their students. In addition to capturing demographics of student participants to facilitate analysis, this survey sought to determine which of the available AI software students were using in different settings and for different tasks. In addition, the students' feelings toward using AI in personal, academic/school, and work situations were questioned. A complete list of survey questions can be found in Appendix A.

DATA ANALYSIS

The survey was offered to 41 different courses across the college. Of the 1,216 students in these courses, 416 responded to the survey for a response rate of 34.21%. Gender, major, and age were used as independent variables for the study. Characteristics of the survey respondents are summarized in Figures 1, 2, and 3 below.

More male students (53.13%) responded to the survey than female students (46.88%). This is depicted in Figure 1.

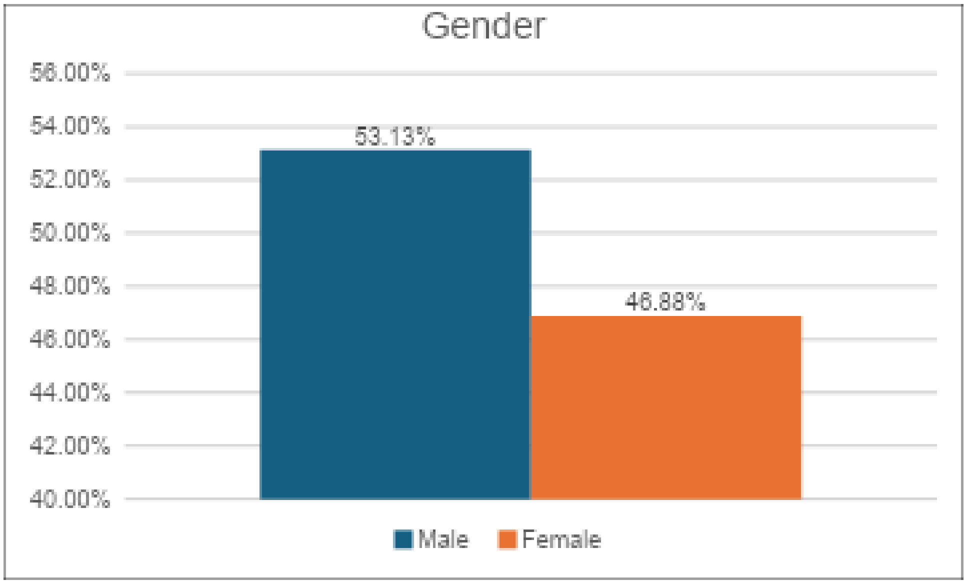

Figure 1. Summary of Students' Gender, N = 416

Over half of the respondents were 18 to 20 years of age (51.44%). Due to the small number of students in the 51 years of age or older group, they were combined with the 41 to 50 years of age group for analysis purposes. The "new" group was renamed to "41 years of age or older." As the students' age increased, the number of students within the different older age groups decreased, with the students being 41 years of age or older having the smallest representation at 2.64%. Figure 2 depicts the different age groups with their respective percentages.

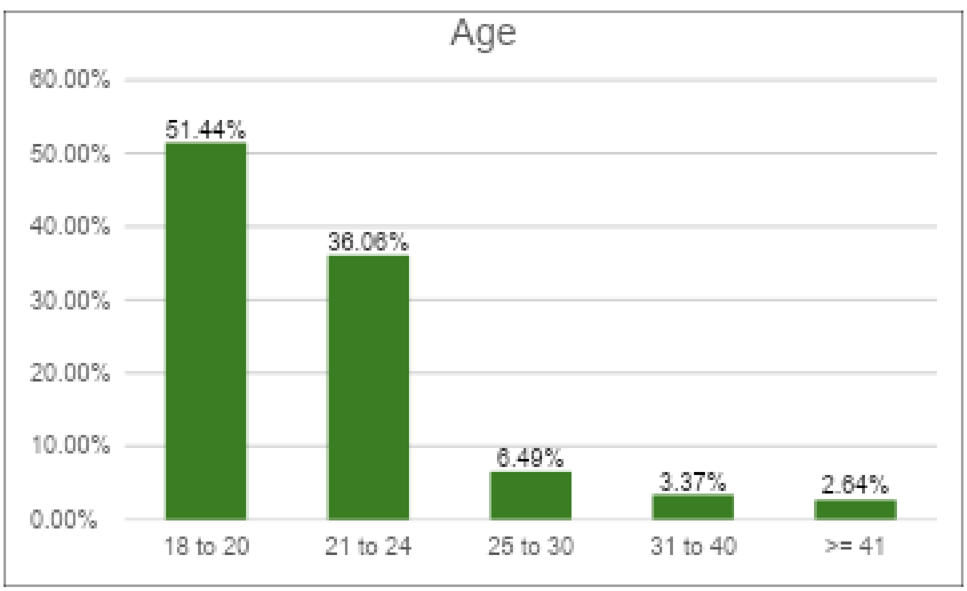

Figure 2. Summary of Students' Age, N = 416

Non-business majors were the largest group responding to the survey at 21.88%. The large number of non-business majors is a result of a computer literacy course taught in the college that is required by several majors across the university. Coming in at a close second were the BSAD (Business Administration) majors (21.15%). ACCT (Accounting) (16.35%), CIS

(Computer Information Systems) (11.78%), MKTG (Marketing) (10.58%), and MNGT (Management) (10.58%) majors were represented. The smallest group of majors was FINC (Finance) at 8.17%.

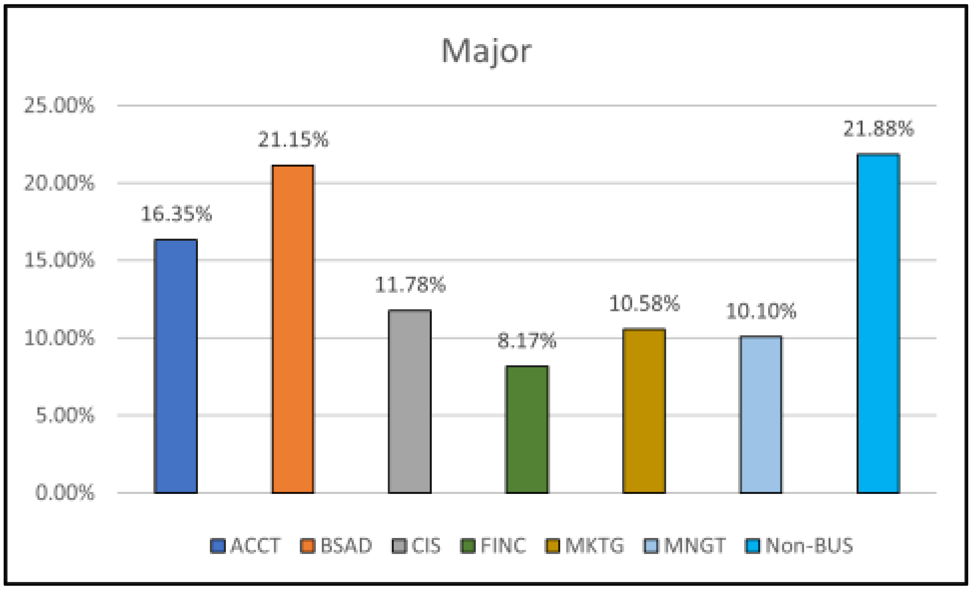

Figure 3. Summary of Students' Major, N = 416

Three dependent variables were used in this study. These included the following questions, which all used a five-point Likert scale (strongly dislike, dislike, neither dislike nor like, like, strongly like) for answer choices.

- What are your feelings about the use of AI for personal reasons
- What are your feelings about the use of AI for school reasons
- What are your feelings about the use of AI for work reasons

The mean and standard deviation for each of the dependent variables are reported in Table 1.

Table 1

Mean and Standard Deviation of Dependent Variables

Question	N	Mean	Std. Dev.
1. What are your feelings about the use of AI for personal reasons?	416	3.65	1.011
2. What are your feelings about the use of AI for school reasons?	416	3.42	1.010
3. What are your feelings about the use of AI for work reasons?	416	3.46	1.072

Of the three questions, “*What are your feelings about the use of AI for personal reasons?”* had the highest mean (*M* = 3.65, *SD* = 1.011), while the dependent variable “*What are your feelings about the use of AI for school reasons?*” had the lowest (*M* = 3.42, *SD* = 1.010).

Independent Samples t-tests and Analysis of Variance

Independent samples t-tests were conducted using the independent variable, **Gender**. All tests were conducted to the .05 level of significance. Relating to the three questions on the survey, hypotheses (H1-H3) were formulated about the differences in the mean of the dependent variables by gender. Two hypotheses in this grouping were found to be statistically significant.

The first hypothesis was do male students feel the same about the question, “*What are your feelings about the use of AI for school reasons?*” as female students? There was a significant difference in the means for males (*M* = 3.54, *SD* = .956) and females (*M* = 3.28, *SD* = 1.054); *t*(414) = 2.586, *p* = 0.010. These results suggest male students had an overall higher belief for using AI in a school setting than the female students.

The second hypothesis was do male students feel the same about the question, “*What are your feelings about the use of AI for work reasons?*” as female students? There was a significant difference in the means for males (*M* = 3.58, *SD* = 1.061) and females (*M* = 3.32, *SD* = 1.071); *t*(414) = 2.444, *p* = 0.015. Here again, the results suggest that the male students had a higher belief in the use of AI in a work setting than the female students. The two statistically significant results can be seen in Table 2 below.

Table 2

Independent Samples t-test

	Males		Females		
	M	SD	M	SD	*t*-test
What are your feelings about the use of AI for school reasons?	3.54	.956	3.28	1.054	2.586
What are your feelings about the use of AI for work reasons?	3.58	1.061	3.32	1.071	2.444

Using the independent variable **Age**, three ANOVA tests were established, where the Likert-type statements were the factors and **Age** was the variable. All tests were conducted to the .05 level of significance. Two of these three hypotheses were found to be statistically significant and can be viewed in Table 3.

Table 3

Significant Analysis of Variance (ANOVA)

What are your feelings about the use of AI for school reasons?

Source	*df*	*SS*	*MS*	*F*	*p*
Between groups	4	16.439	4.110	4.152	.003
Within groups	411	406.782	.990		
Total	415	423.221			

What are your feelings about the use of AI for work reasons?

Source	*df*	*SS*	*MS*	*F*	*p*
Between groups	4	16.582	4.145	3.698	.006
Within groups	411	460.724	1.121		
Total	415	477.305			

For the statement, "*What are your feelings about the use of AI for **school** reasons?",* there was a statistically significant difference between groups as determined by one-way ANOVA (F (4, 411) = 4.152, p = .003). Because of unequal group sizes, Fisher's LSD post hoc test was used to determine the nature of the difference between members of each **Age** group; this analysis revealed that there was a statistically significant difference between the mean of the 18- to 20-year-old students (M = 3.27, SD = .970) and the mean of the 21- to 24-year-old students (M = 3.66, SD = .954). In addition, analysis revealed that there was a statistically significant difference between the mean of the 21- to 24-year-old students (M = 3.66, SD = .954) and the mean of the 31- to 40-year-old students (M = 3.00, SD = 1.038).

For the statement, "*What are your feelings about the use of AI for **work** reasons?",* there was a statistically significant difference between groups as determined by one-way ANOVA (F (4, 411) = 3.698, p = .006). Because of unequal group sizes, Fisher's LSD post hoc test was used to determine the nature of the difference between members of each **Age** group; this analysis revealed that there was a statistically significant difference between the mean of the 18- to 20-year-old students (M = 3.28, SD = 1.036) and the mean of the 21- to 24-year-old students (M = 3.71, SD = 1.059).

Using the independent variable **Major**, three ANOVA tests were established, where the Likert-type statements were the factors and **Major** was the variable. All tests were conducted to the .05 level of significance. Two of these three hypotheses were found to be statistically significant and can be viewed in Table 4.

Table 3

Significant Analysis of Variance (ANOVA)

What are your feelings about the use of AI for personal reasons?

Source	*df*	*SS*	*MS*	*F*	*p*
Between groups	6	20.425	3.404	3.446	.002
Within groups	409	404.035	.988		
Total	415	424.459			

What are your feelings about the use of AI for work reasons?

Source	*df*	*SS*	*MS*	*F*	*p*
Between groups	6	28.900	4.817	4.393	.000
Within groups	409	448.405	1.096		
Total	415	477.305			

For the statement, "*What are your feelings about the use of AI for* ***personal*** *reasons?",* there was a statistically significant difference between groups as determined by one-way ANOVA (F (6,409) = 3.446, p = .002). Because of unequal group sizes, Fisher's LSD post hoc test was used to determine the nature of the difference between members of each **Major** group; this analysis revealed that there was a statistically significant difference between the mean of the ACCT majors (M = 3.65, SD = .927) and the mean of the non-business majors (M = 3.32, SD = 1.010). In addition, analysis revealed that there was a statistically significant difference between the mean of the BSAD students (M = 3.56, SD = .981) and the mean of the MNGT students (M = 3.95, SD = 1.038). Another statistically significant difference revealed was between the mean of the CIS majors (M = 3.80, SD = .979) and the mean of the non-business majors (M = 3.32, SD = 1.010). The mean of the FINC majors (M = 3.91, SD = .793) was statistically significant different than the mean of the non-business majors (M = 3.32, SD = 1.010). The last statistically significant difference revealed was between the mean of the MKTG majors (M = 3.89, SD = 1.185) and the mean of the non-business majors (M = 3.32, SD = 1.010).

For the statement, "*What are your feelings about the use of AI for* ***work*** *reasons?",* there was a statistically significant difference between groups as determined by one-way ANOVA (F (6,409) = 4.393, p = .000). Because of unequal group sizes, Fisher's LSD post hoc test was used to determine the nature of the difference between members of each **Major** group; this analysis revealed that there was a statistically significant difference between the mean of the ACCT majors (M = 3.43, SD = .967) and the mean of the MNGT majors (M = 3.83, SD = 1.010). In addition, analysis revealed that there was a statistically significant difference between the mean of the BSAD students (M = 3.58, SD = 1.014) and the mean of the non-business students (M =

3.03, *SD* = .971). Another statistically significant difference revealed was between the mean of the CIS majors (*M* = 3.39, *SD* = 1.037) and the mean of the MNGT majors (*M* = 3.83, *SD* = 1.010). The mean of the FINC majors (*M* = 3.59, *SD* = 1.048) was statistically significant different than the mean of the non-business students (*M* = 3.03, *SD* = .971). The last statistically significant difference revealed was between the mean of the MKTG majors (*M* = 3.77, *SD* = 1.379) and the mean of the non-business majors (*M* = 3.03, *SD* = .971).

AI Usage in Life

The students were asked to report whether they were using AI in various parts of their life, including personal, academic/school, and work. Because not all the students have a job, the students were asked if they had a job. Of the 416 students responding to the survey, 304 reported having a job. The "usage in work life" was only answered by students having a job. AI usage is very high in both personal life (72.60%) and in academic/school life, (78.13%). Work usage was the opposite, with reported usage at 29.93%. Table 5 displays the students' responses to usage.

Table 5

Usage of AI in Life

Situation	Yes	No
Personal life, N = 416	72.60%	27.40%
Academic/school life, N = 416	78.13%	21.88%
Work life, N = 304	29.93%	70.07%

The students were asked to choose ways they were using AI in their personal, academic/school, and work life. Table 6 displays some of their responses in the three areas.

Table 6

Students' Usage of AI in Their Life

Personal Life
Ask for interview questions and how to answer
Ask for medical terminology and what questions you should ask your doctor
Ask for movie times at a local theater
Ask for weather information
Ask to help with a vacation itinerary
Ask for a workout/diet plan

Ask questions that would take some research time in google
Generate images
Help with resume
Look up random facts that I'm curious about--recipes, tv shows, books
Someone to talk to
Sourcing articles that are hidden behind a paywall
Used to answer a message someone sent me
Deciding what to eat for a meal?
Writing a caption for a Facebook post
Writing code for a personal home lab
Academic/School Life
Use as a study tool/tutor
Generate good synonyms for my writing
Help with group projects
Help with homework/assignments
Help with quizzes and exams
Help in online classes
Proofread my work and make grammar corrections and other suggestions
Start an assignment, then I personalize it with my own research and thoughts
Work Life
Add items to my work calendar
Compare documents
Create a To-Do list
Create templates
Proofread and edit an email
Search databases more efficiently

Summarize meetings
Use previous sales to predict future sales and the ordering required

AI Usage in Academic/School Settings

Digging deeper into the academic/school usage of AI, the survey also captured whether students used AI in various academic/school situations. Of the seven situations presented to the students, AI was not used in most settings. Only when “solving math problems” at 62.50% and “working on homework assignments” at 60.58%, did more students report using AI than not. In addition, “Solving math problems” had the highest “yes” response at 62.50%, while “writing a speech” had the lowest “yes” response at 18.03%. The highest “no” response was “writing a speech” at 81.97” and the lowest “no” response was for “solving math problems” at 37.50%. Table 7 displays the results of whether students are choosing to use AI or not in certain academic situations.

Table 7

Is AI Used in Certain Academic Situations

Situation	Yes	No
Creating a presentation	29.33%	70.67%
Writing a long report	42.79%	57.21%
Writing a short report	39.66%	60.34%
Creating notecards for studying	48.08%	51.92%
Solving math problems	62.50%	37.50%
Working on homework assignments	60.58%	39.42%
Writing a speech	18.03%	81.97%

If they did use AI, they were given a list of choices to pick from for their responses. The list of AI software choices was a result of a previous research project conducted by the authors (Anonymous, 2025). The AI software included the following: ChatGPT, Google Gemini, Grammarly, Microsoft Copilot, Microsoft Editor, NoteGPT, Perplexity.ai, and Quizlet.

A question concerning AI software usage was presented for each of the situations mentioned in Table 7. The first situation was the following: “W*hen creating slides for a* ***presentation****, which of the following AI software choices have you used? (Select all that apply).*” As illustrated in Figure 4, of the 29.33% of students using AI for this task, ChatGPT was overwhelmingly the most popular AI software used, with 39.4% of the respondents reporting usage. NoteGPT received the smallest percentage of usage at 0.4%.

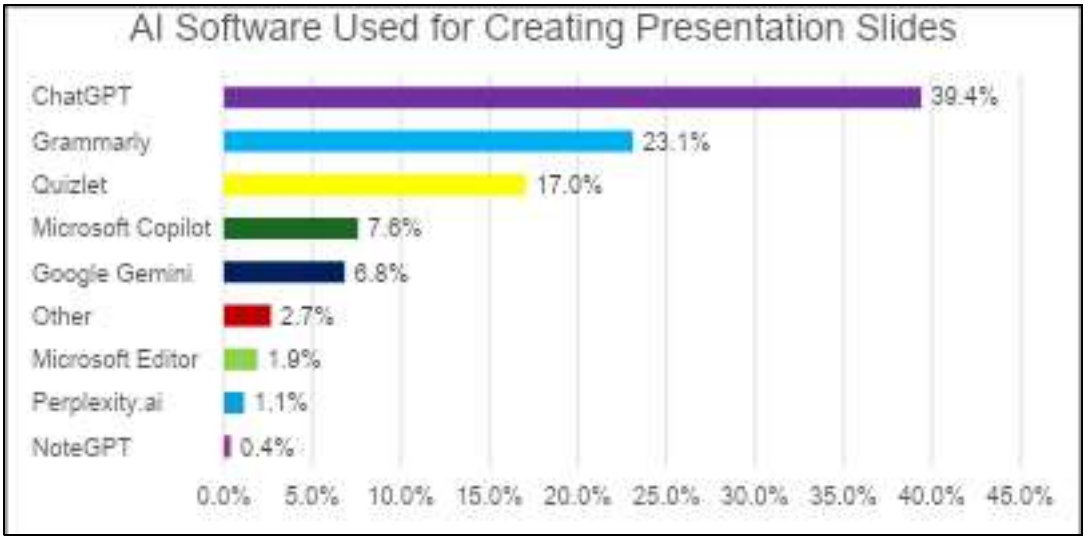

Figure 4. AI Software Used for Creating Presentation Slides

The second situation was the following: "W*hen writing a **long report**, which of the following AI software choices have you used? (Select all that apply.)*" As illustrated in Figure 5, of the 42.79% of students using AI for this task, ChatGPT was the most popular AI software used, with 41.8% of the students reporting usage. NoteGPT received the smallest percentage of usage at 0.3%.

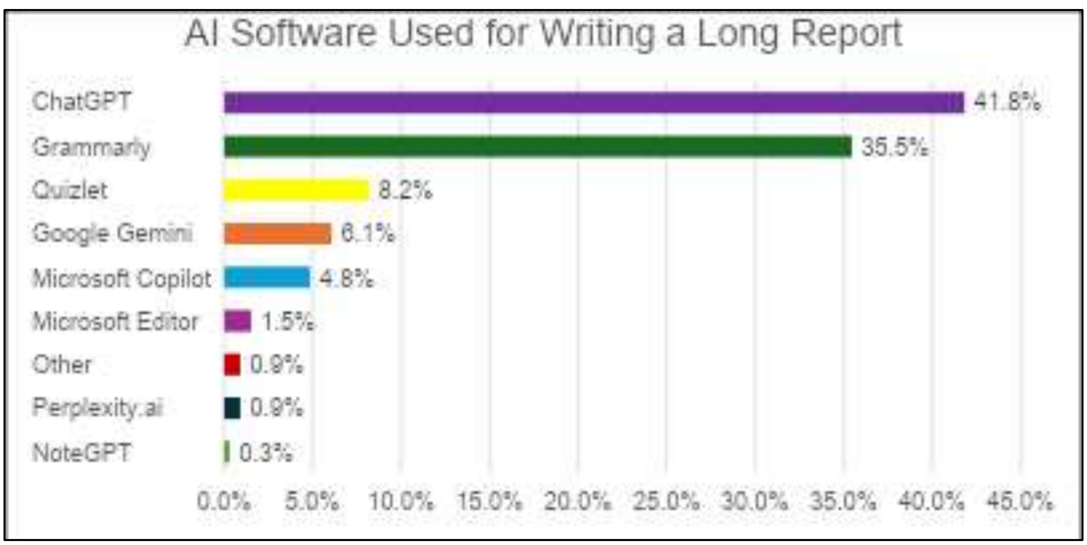

Figure 5. AI Software Used for Writing a Long Report

The third question was the following: "W*hen writing a **short report**, which of the following AI software choices have you used? (Select all that apply.)*" As illustrated in Figure 6, the results were very similar to the "long report" usage. For the 39.66% of students using AI for this task, ChatGPT was the most popular AI software used, with 43.6% of the students reporting usage. "Other" and NoteGPT received the smallest percentage of usage, both at 0.3%.

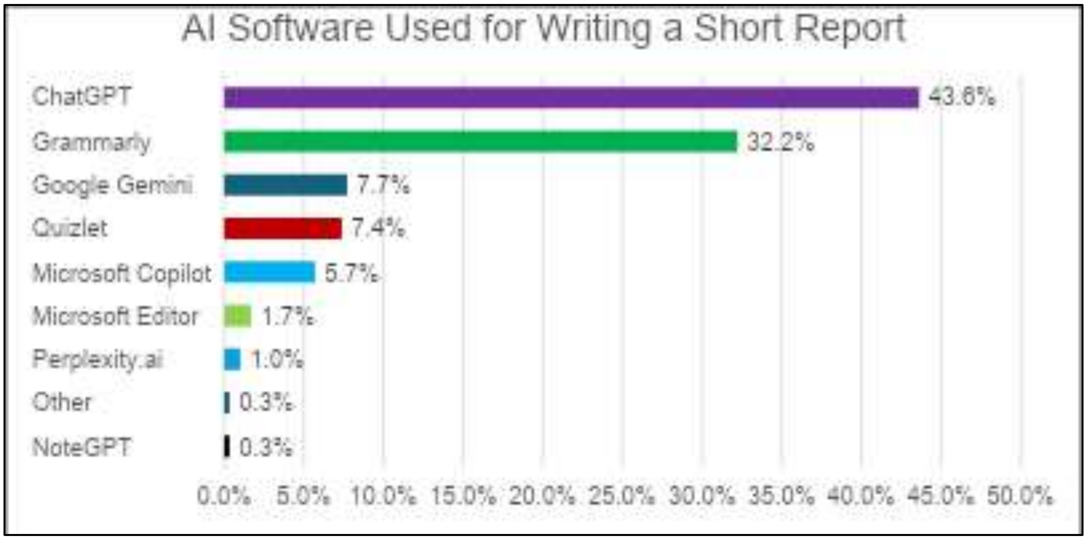

Figure 6. AI Software Used for Writing a Short Report

The fourth situation was the following: "W*hen creating* ***notecards*** *for studying, which of the following AI software choices have you used? (Select all that apply.)*" As illustrated in Figure 7, a different leader was chosen. Of the 48.08% of students using AI for this task, Quizlet was the most popular AI software used, with 46.2% of the students reporting usage. Perplexity.ai came in at the bottom of the list with only 0.3% usage.

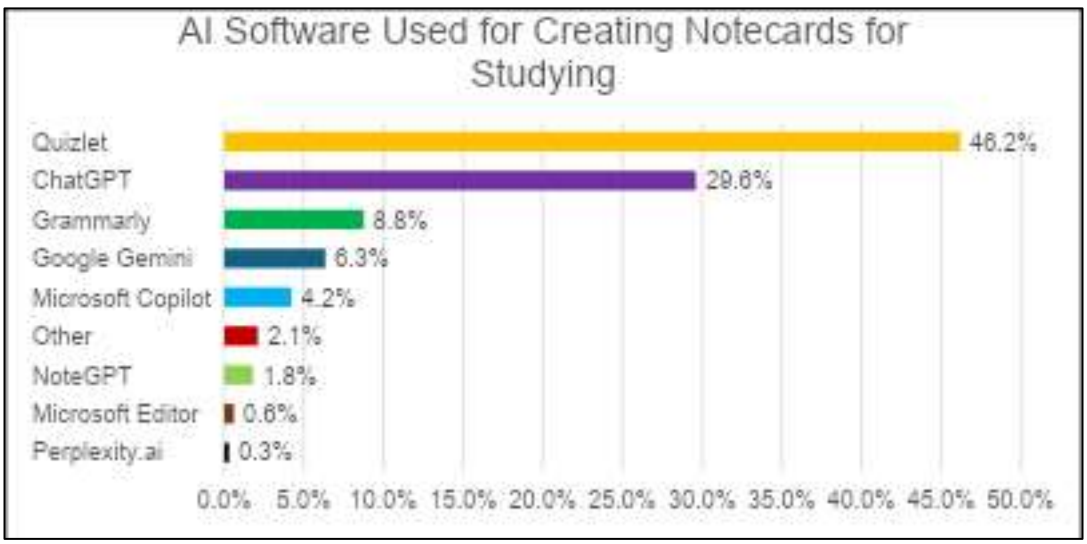

Figure 7. AI Software Used for Creating Notecards for Studying

The fifth situation was the following: "W*hen solving* ***math problems****, which of the following AI software choices have you used? (Select all that apply.)*" Results illustrated in Figure 8 show that for the 62.5% of students using AI for this task, ChaptGPT was the clear leader with 57.3% of usage, which was 42.4% above the next highest reported chosen software, Google Gemini (14.9%). The least used software was Perplexity.ai at 0.9%. The "other" choice consisted of several math-oriented AI software choices.

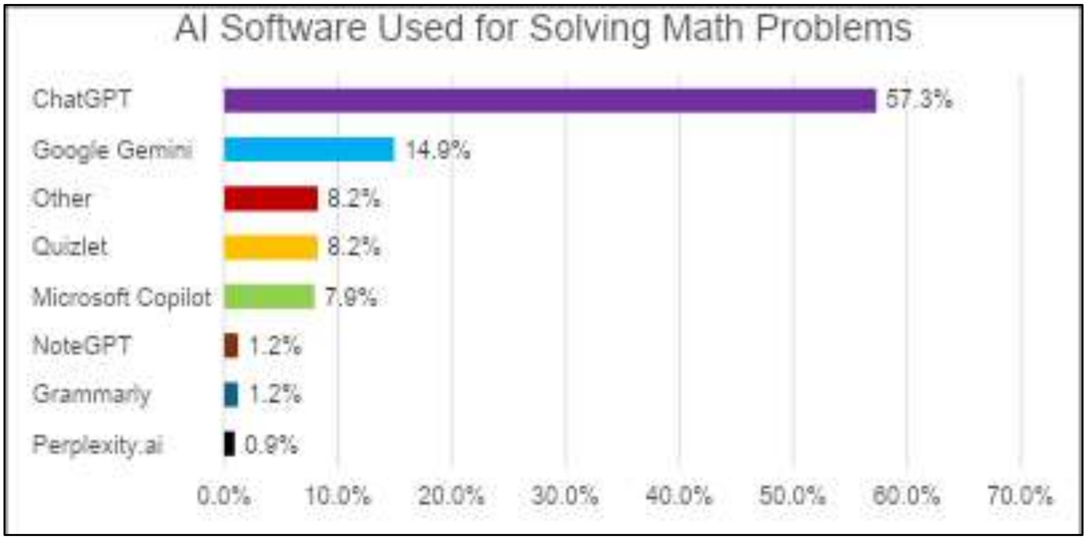

Figure 8. AI Software Used for Solving Math Problems

The sixth situation was the following: *"In general, when working on **homework assignments**, which of the following AI software choices have you used? (Select all that apply.)*" As illustrated in Figure 9, of the 60.58% of students using AI for this task, ChatGPT was the most popular AI software used, with 43.7% of the students reporting usage. NoteGPT and Perpleity.ai received the smallest percentage of usage, both at 0.9%.

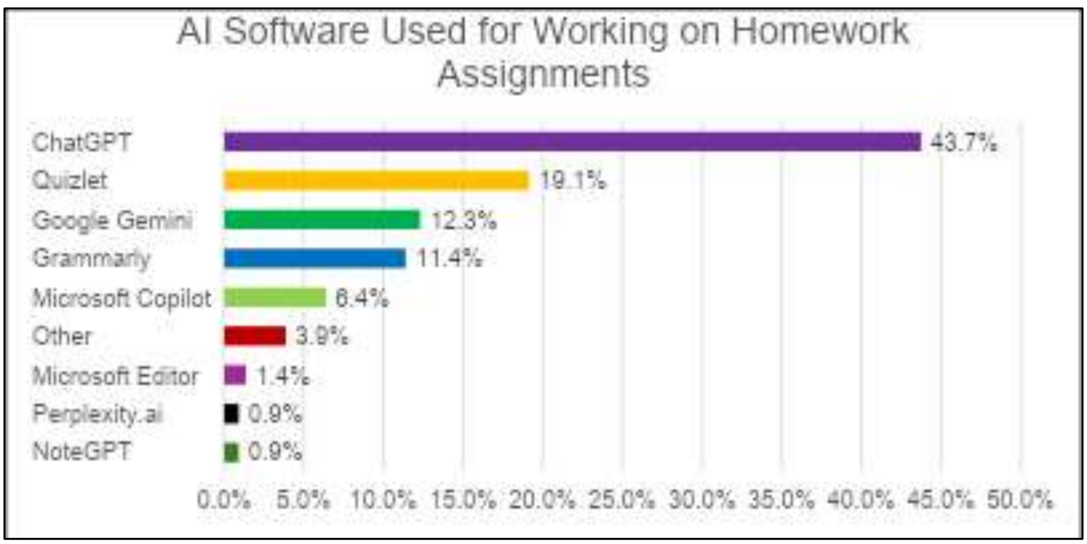

Figure 9. AI Software Used for Working on Homework Assignments

For the last situation, *"When writing a **speech**, which of the following AI software choices have you used? (Select all that apply.)*", results illustrated in Figure 10 depict ChatGPT as the most popular AI software used. Of the 18.03% of students using AI for this task, 55.5% were using ChatGPT. NoteGPT and "Other" received the smallest percentage of usage, both at 0.8%.

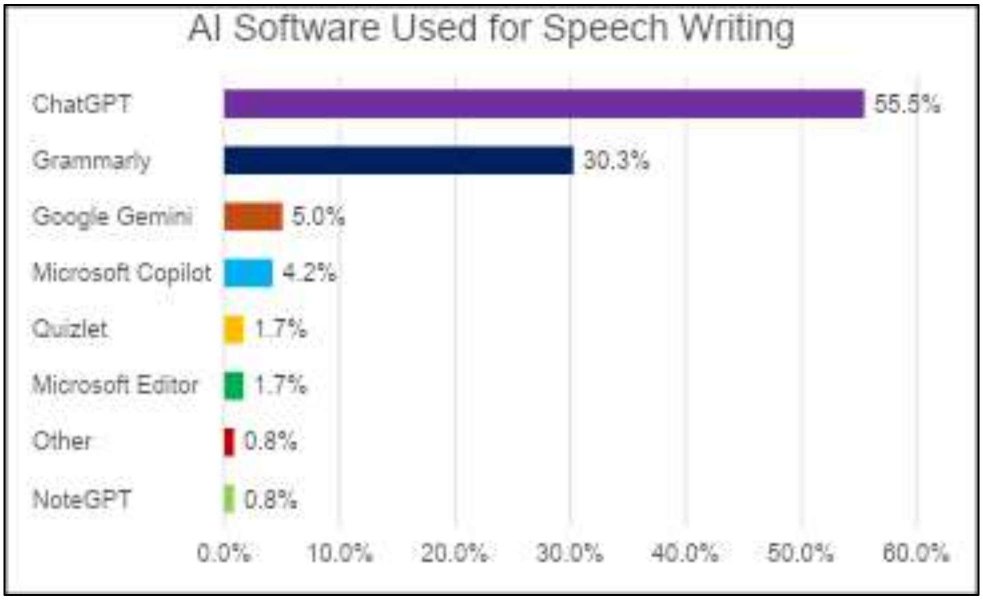

Figure 10. AI Software Used for Speech Writing

In six of the seven academic usage questions presented in the survey, ChatGPT was the most frequent AI tool used by the responding students. The authors' opinions on the popularity of ChatGPT and Quizlet include ease of use, "word of mouth" spread, low cost (free/inexpensive), and shareable content, to name a few reasons.

Knowledge of School Policies

As a final research area, the students were asked to report whether they were aware of any AI policies at their university or in their classes. For the question, *"Do you know if your university has a standard **AI policy**?",* 89.18% of the students reported they were aware of a university standard AI policy. *"Is there a clear **AI expectation or policy** stated in any of the course syllabi?"* was the other question presented to students. Of the respondents, 92.07% reported knowing of an expectation or policy, while 7.93% were unaware. Table 8 displays the responses.

Table 8

School AI Policies

Policy	Yes	No
Do you know if your university has a standard **AI policy**?	89.18%	10.82%
Is there a clear **AI expectation or policy** stated in any of the course syllabi?	92.07%	7.93%

CONCLUSIONS AND IMPLICATIONS

The current study reports the findings from a student survey at a mid-sized public university in the southern United States. These students were enrolled in College of Business courses regardless of their major. Of the students responding, the males (53.13% of respondents) had stronger positive feelings for the use of AI for school (*M* = 3.54) and work reasons (*M* = 3.58) than the female students for school reasons (*M* = 3.28) and for work reasons (*M* = 3.32), resulting in statistically significant findings.

Findings show that the students in the age group of 21- to 24-year-old students (*M* = 3.66) had the highest feelings toward the use of AI in personal, academic/school, and work life compared to the other age groups. Their comparison was statistically significant to both 18- to 20-year-old age group (*M* = 3.27) and the 31- to 40-year-old group (*M* = 3.00) for school reasons. In addition, the 21- to 24-year-old students' comparison (*M* = 3.71) to the 18- to 20-year-old age group (*M* = 3.28) was statistically significant.

Management (MNGT) students had the highest positive feelings toward the use of AI in personal, academic/school, and work reasons compared to the other majors. When looking at the findings for use of AI in personal reasons, several statistically significant comparisons of means were made. These include Accounting (ACCT) majors (*M* = 3.65) to non-business majors (*M* = 3.32), Business Administration (BSAD) students (*M* = 3.56) to Management (MNGT) students (*M* = 3.95), Computer Information Systems (CIS) majors (*M* = 3.80) to non-business majors (*M* = 3.32), Finance (FINC) majors (*M* = 3.91) to non-business majors (*M* = 3.32), and Marketing (MKTG) majors (*M* = 3.89, *SD* = 1.185) to non-business majors (*M* = 3.32).

Several statistically significant comparisons of means for the use of AI in work-related reasons were made. These findings include ACCT majors (*M* = 3.43) to MNGT majors (*M* = 3.83), BSAD students (*M* = 3.58) to non-business students (*M* = 3.03), CIS majors (*M* = 3.39) to MNGT majors (*M* = 3.83), FINC majors (*M* = 3.59) to non-business students (*M* = 3.03), and MKTG majors (*M* = 3.77) to non-business majors (*M* = 3.03).

Approximately three-fifths of survey respondents were using AI software to complete homework assignments and to solve math problems. Almost one-half of respondents were using AI to help create notecards for studying. Approximately two-fifths were using AI to help them prepare long reports and short reports. Respondents used AI less frequently to help create a presentation (29.33%), and to write a speech (18.03%). These findings are somewhat below the recent findings by Legatt (2025) and Reyes (2025). Based on recent research discussed in the review of literature, the authors anticipate these percentages would all increase if the survey were repeated in the future.

ChatGPT was the most frequently used AI tool in use by respondents for presentations, long and short report writing, solving math problems, working on homework assignments, and writing speeches. Quizlet, however, was the most frequently reported AI tool when creating notecards for studying. The authors speculate that the usage will continue to increase over time, with specialized tools, such as Quizlet, being developed. AI tools are being incorporated into current software, such as Microsoft Office, having Microsoft Editor as part of Word and Speaker Coach in PowerPoint. Microsoft Editor can be added as an extension of both Microsoft Edge and Chrome browsers (Anonymous, 2023).

Regarding the university's AI policies and AI policies of professors, a high percentage of student respondents (89.18%) reported knowing the university has a standard AI policy, and 92.07% reported reading an AI expectation or policy in at least one course syllabus. While the numbers appear positive, universities and faculty still struggle to balance AI in the classroom and students' expected knowledge of AI tools upon graduation. The authors plan to share findings with faculty within the College of Business at their institution and survey faculty in the future regarding their usage of AI in business courses and curricula to prepare students for the work environment.

Adding these survey findings to the body of literature about the use of AI by students in various settings provides additional support for the incorporation of AI into their lives. The challenge for faculty is to effectively align AI tools with pedagogical goals while maintaining ethical standards and preparing students for the workforce.

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APPENDIX A
Student Usage of AI

Please find below a quick survey concerning your thoughts and usage of AI. Your participation in the survey is completely voluntary. You are not obligated to answer any of the questions, and you may terminate the survey at any time. Your participation is anonymous, and the results will be kept confidential. The survey will take approximately 5-8 minutes to complete. The results of the survey will be presented at a conference in 2026. If you are willing to participate, please enter your student email address.
Email____

Consent to Participate
Do you consent to participate in this survey?

- ○ Yes
- ○ No – exit survey

Use in **presentations**
Have you used AI to assist in creating a **presentation**?

- ○ Yes
- ○ No – move to long report section

Presentation – Choices of AI software
When creating slides for a **presentation**, which of the following AI software choices have you used? (Select all that apply)

- □ ChatGPT
- □ Google Gemini
- □ Grammarly
- □ Microsoft Copilot
- □ Microsoft Editor
- □ NoteGPT
- □ Perplexity.ai
- □ Quizlet
- □ Other: ____

Use in **long report**
Have you used AI to assist in writing a **long report**?

- ○ Yes
- ○ No – move to short report section

Long Report – Choices of AI software
When writing a **long report**, which of the following AI software choices have you used? (Select all that apply)

- □ ChatGPT
- □ Google Gemini
- □ Grammarly
- □ Microsoft Copilot
- □ Microsoft Editor

- ☐ NoteGPT
- ☐ Perplexity.ai
- ☐ Quizlet
- ☐ Other: ____

Use in **short report**
Have you used AI to assist in writing a **short report**?
- ○ Yes
- ○ No – move to notecards section

Short Report – Choices of AI software
When writing a **short report**, which of the following AI software choices have you used? (Select all that apply)
- ☐ ChatGPT
- ☐ Google Gemini
- ☐ Grammarly
- ☐ Microsoft Copilot
- ☐ Microsoft Editor
- ☐ NoteGPT
- ☐ Perplexity.ai
- ☐ Quizlet
- ☐ Other: ____

Use in creating **notecards**
Have you used AI to assist in creating **notecards** for studying?
- ○ Yes
- ○ No – move to math problems section

Notecards – Choices of AI software
When creating **notecards**, which of the following AI software choices have you used? (Select all that apply)
- ☐ ChatGPT
- ☐ Google Gemini
- ☐ Grammarly
- ☐ Microsoft Copilot
- ☐ Microsoft Editor
- ☐ NoteGPT
- ☐ Perplexity.ai
- ☐ Quizlet
- ☐ Other: ____

Use in solving **math problems**
Have you used AI when solving **math problems**?
- ○ Yes
- ○ No - move to homework section

Math Problems – Choices of AI software
When solving **math problems**, which of the following AI software choices have you used? (Select all that apply)

- ◻ ChatGPT
- ◻ Google Gemini
- ◻ Grammarly
- ◻ Microsoft Copilot
- ◻ Microsoft Editor
- ◻ NoteGPT
- ◻ Perplexity.ai
- ◻ Quizlet
- ◻ Other: ____

Use in working **homework assignments**
Have you used AI when working on **homework assignments**?

- ○ Yes
- ○ No – move to speech section

Homework Assignments – Choices of AI software
In general, when working on **homework assignments**, which of the following AI software choices have you used? (Select all that apply)

- ◻ ChatGPT
- ◻ Google Gemini
- ◻ Grammarly
- ◻ Microsoft Copilot
- ◻ Microsoft Editor
- ◻ NoteGPT
- ◻ Perplexity.ai
- ◻ Quizlet
- ◻ Other: ____

Use in writing a **speech**
Have you used AI when writing a **speech**?

- ○ Yes
- ○ No – move to AI expectation or policy section

Writing a Speech – Choices of AI software
When writing a **speech**, which of the following AI software choices have you used? (Select all that apply)

- ◻ ChatGPT
- ◻ Google Gemini
- ◻ Grammarly
- ◻ Microsoft Copilot
- ◻ Microsoft Editor
- ◻ NoteGPT
- ◻ Perplexity.ai

- ☐ Quizlet
- ☐ Other: ____

AI expectation or policy
Do you know if your university has a standard **AI policy**?

- ○ Yes
- ○ No

Is there a clear **AI expectation or policy** stated in any of the course syllabi?

- ○ Yes
- ○ No

Course Syllabi mentioning an AI policy
Which course(s) mentions an AI policy in the syllabi?

____

Your feeling about AI usage
What are your feelings about the use of AI for **personal reasons**?

- ○ Strongly dislike
- ○ Dislike
- ○ Neither dislike nor like
- ○ Like
- ○ Strongly like

What are your feelings about the use of AI for **school reasons**?

- ○ Strongly dislike
- ○ Dislike
- ○ Neither dislike nor like
- ○ Like
- ○ Strongly like

What are your feelings about the use of AI for **work reasons**?

- ○ Strongly dislike
- ○ Dislike
- ○ Neither dislike nor like
- ○ Like
- ○ Strongly like

Use of AI in your personal like
Have you used AI in your **personal life**?

- ○ Yes
- ○ No – move to academic / school life section

Personal Life Choices
Ways in which you have used AI in your **personal life**…

- ☐ Use Google Lens to identify plants
- ☐ Ask for movie times at a local theater

- ◻ Ask for concert information for my favorite artist
- ◻ Ask for recipes that contain a specific ingredient
- ◻ Ask for weather information
- ◻ Ask for medical terminology and what questions you should ask your doctor
- ◻ Other: ____

Use of AI in your academic / school life

Have you used AI in your **academic / school life**?

- ○ Yes
- ○ No – move to work section

Academic / School Life Choices

Ways in which you have used AI in your **academic / school life**…

- ◻ In online classes
- ◻ In traditional in-person classes
- ◻ As a study tool/tutor
- ◻ Start an assignment, then I personalize it with my own research and thoughts
- ◻ Proofread my work and make grammar corrections and other suggestions
- ◻ Help with homework/assignments
- ◻ Help with quizzes and exams
- ◻ Help with group projects
- ◻ Other: ____

Work Situation

Do you have a job?

- ○ Yes
- ○ No – move to demographics section

Use of AI in your work like

Have you used AI in your **work life**?

- ○ Yes
- ○ No – move to demographics section

Work Life Choices

Ways in which you have used AI in your **work life**…

- ◻ Proofread and edit an email
- ◻ Ask for directions to a specific address
- ◻ Add items to my work calendar
- ◻ Create a To-Do-list
- ◻ Summarize meetings
- ◻ Create templates
- ◻ Compare documents
- ◻ Other: ____

DEMOGRAPHICS

Gender

- Male
- Female

Age

- 18 to 20 years of age
- 21to 24 years of age
- 25 to 30 years of age
- 31 to 40 years of age
- 41 to 50 years of age
- 51 years of age or older

Major

- Accounting
- Business Administration
- Computer Information Systems
- Finance
- Management
- Marketing
- Non-business major

Thank you for participating in this survey. Your answers have been recorded.

UNIVERSAL NEW INTEROPERABLE CONTROL BLOCKCHAIN PROTOCOL (UNIC-BP)

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ABSTRACT

The convergence of metaverse platforms, Internet of Things (IoT), and smart public infrastructure has created an urgent demand for universal, privacy-preserving, and quantum-secure authentication frameworks. While blockchain has emerged as a candidate technology for decentralized identity management, most existing protocols remain limited: they address security, privacy, or interoperability in isolation, and thus fail to provide a holistic, future-proof foundation for authentication across heterogeneous digital environments. Moreover, the advent of quantum computing threatens to undermine widely deployed cryptographic primitives, exacerbating the risks associated with fragmented digital identities and siloed authentication systems. This paper introduces the Universal New Interoperable Control Blockchain Protocol (UNIC-BP), a modular and extensible blockchain protocol designed to unify four critical pillars of next-generation authentication: quantum-resistant cryptography, protocol-enforced zero-knowledge proofs, sustainable Proof-of-Space-Time consensus, and native cross-chain interoperability. UNIC-BP's layered architecture is designed for adaptability, enabling continuous upgrades as cryptographic standards and digital ecosystems evolve. By enforcing privacy-by-default through zero-knowledge proofs, embedding post-quantum signatures and key exchanges, and enabling trustless cross-chain state validation, UNIC-BP establishes a scalable and resilient authentication layer for users, devices, and AI agents. We analyze UNIC-BP's security, privacy, and scalability properties, showing how it mitigates quantum threats, ensures confidential and selective disclosure of credentials, and achieves sustainable consensus suitable for global-scale deployment. Through case studies in multi-metaverse authentication, IoT infrastructure, healthcare, finance, and AI identity management, we demonstrate its applicability across domains. UNIC-BP is positioned as a universal authentication foundation that advances the vision of secure, interoperable, and user-centric digital societies in the quantum era.

Keywords: Information Systems, Blockchain, Interoperability, Quantum-Resistant, Privacy, Metaverse, Identity, Consensus

INTRODUCTION

Digital transformation is accelerating, with interconnected platforms such as the metaverse, Internet of Things (IoT), and smart public infrastructure reshaping daily life, commerce, and governance. This expansion drives a pressing need for authentication frameworks that are not only secure and scalable but also privacy-preserving and universally interoperable (Belchior et al., 2022; Ben-Sasson et al., 2014; Nakamoto, 2008). However, legacy blockchain systems suffer from persistent limitations: most lack quantum resilience, treat privacy as an auxiliary feature rather than a protocol-level property and perpetuate fragmented identity silos that undermine usability (Reed et al., 2020; Zhang et al., 2019).

The emergence of quantum computing exacerbates these vulnerabilities, as widely used cryptographic primitives (e.g., ECDSA, RSA) are susceptible to Shor's algorithm. Simultaneously, the fragmentation of digital identity across applications and blockchains results in user inconvenience, increased attack surfaces, and operational inefficiencies.

This paper presents the Universal New Interoperable Control Blockchain Protocol (UNIC-BP), which unifies quantum-resistant cryptography, privacy-by-default through zero-knowledge proof (zk-SNARKs), sustainable Proof-of-Space-Time consensus, and built-in cross-chain interoperability. UNIC-BP is designed as a foundation for user-, device-, and AI-centric authentication and credential management across next-generation digital networks.

1. Related Work

1.1 Blockchain Consensus Evolution

First-generation blockchains such as Bitcoin introduced Proof-of-Work (PoW) for consensus, providing security but incurring high energy costs and scalability bottlenecks (Nakamoto, 2008). Proof-of-Stake (PoS) improved efficiency but brought centralization and "nothing-at-stake" risks (Belchior et al., 2022). Proof-of-Space-Time (PoST) consensus leverages storage over time, enabling secure and sustainable consensus suitable for global-scale networks (Cohen & Pietrzak, 2018; Moran & Orlov, 2019).

1.2 Privacy in Blockchain

Privacy remains a major challenge in most public blockchains. Bitcoin and Ethereum are pseudonymous but vulnerable to data analysis. Zcash's integration of zk-SNARKs allowed confidential transactions, though privacy remains optional in most systems (Ben-Sasson et al., 2014). Advances in privacy-preserving decentralized identity leverage zero-knowledge proofs for selective disclosure and compliance, but most implementations are not enforced at the protocol level (Fernandez-Carames & Fraga-Lamas, 2020; Zhang et al., 2019).

1.3 Quantum-Resistant Cryptography

Quantum computing is expected to render classical cryptographic schemes obsolete. Lattice-based, post-quantum algorithms are under standardization by NIST and offer promising defenses against quantum attacks (Dang et al., 2024; Yang et al., 2024). However, their integration into production blockchains and identity systems is still limited.

1.4 Decentralized Identity and Interoperability

Decentralized Identifiers (DIDs) and Verifiable Credentials (VCs) are emerging as the basis for user-controlled, cross-platform identity. Current implementations often lack integration with privacy technologies and robust interoperability, and most rely on classical cryptography (Allen, 2016; Reed et al., 2020; Zhang et al., 2019). Interoperability protocols (e.g., Cosmos, Polkadot) enable asset transfers and messaging between blockchains but seldom unify decentralized identity or enforce privacy and quantum resistance (Al-Breiki et al., 2020).

2. UNIC-BP Protocol Architecture

UNIC-BP is designed as a four-layer, modular blockchain protocol, allowing for independent upgrades and integration with emerging technologies. Architecture addresses the fundamental pillars of security, privacy, sustainability, and interoperability.

2.1 Consensus Layer: Proof-of-Space-Time

UNIC-BP's base layer implements PoST, where network nodes provide cryptographic proof of allocated storage over time, replacing wasteful computation with sustainable resource commitments (Cohen & Pietrzak, 2018; Moran & Orlov, 2019). This dramatically reduces energy consumption compared to PoW and supports broad validator participation, making it suitable for IoT and public infrastructure applications. Dynamic difficulty adjustment and slashing ensure security and incentivize honest behavior. PoST is inherently democratizing, as storage is widely available and less susceptible to hardware centralization.

2.2 Privacy Layer: Protocol-Enforced Zero-Knowledge Proofs

UNIC-BP integrates zk-SNARKs as a core feature—**not** as an optional add-on. All transactions, identity proofs, and credential operations are shielded by default, enforcing confidentiality for transactional data and identity claims (Ben-Sasson et al., 2014; Zhang et al., 2019). Selective disclosure allows users to prove attributes (e.g., age, citizenship) without exposing unrelated personal data, supporting regulatory compliance and user consent. This layer is modular, allowing adoption of new primitives (e.g., zk-STARKs) for post-quantum privacy as technologies mature.

2.3 Security Layer: Quantum-Resistant Cryptography

UNIC-BP employs lattice-based digital signatures and key exchanges as standardized by NIST (Dang et al., 2024; Yang et al., 2024). All DIDs, credentials, and validator keys are generated using post-quantum algorithms, ensuring resistance to both classical and quantum adversaries. Hybrid cryptography supports migration, while forward secrecy and threshold cryptography enhance overall protocol security, especially for multi-signature wallets and consensus participation.

2.4 Interoperability Layer: Cross-Chain and DID Integration

UNIC-BP's top layer provides native cross-chain state verification and a universal, privacy-preserving DID system. Lightweight clients for major chains (Ethereum, Cosmos, Polkadot, etc.) enable trustless external state validation (Al-Breiki et al., 2020). Secure relays and Merkle proofs facilitate atomic swaps, asset bridging, and cross-chain smart contracts.
DIDs are anchored by quantum-resistant keys, and credentials are issued/verified with zero-knowledge proofs, ensuring seamless, privacy-preserving identity portability across platforms—spanning metaverse, IoT, public infrastructure, and legacy IT systems (Reed et al., 2020; Zhang et al., 2019).

3. Decentralized Authentication and Identity Management

UNIC-BP enables users, organizations, devices, and AI agents to generate DIDs secured by post-quantum public/private keys. Registration on-chain establishes tamper-resistant identity anchors. Issuers (governments, enterprises, universities) provide verifiable credentials, signed with quantum-resistant algorithms and validated using zk-proof—enabling trustless, privacy-preserving authentication.

Selective disclosure allows users to reveal only necessary attributes, supporting GDPR and global privacy regulations (Fernandez-Carames & Fraga-Lamas, 2020). The native compatibility with global standards ensures future interoperability.

3.1 Cross-Platform Usability

UNIC-BP eliminates redundant registrations and enables single sign-on across diverse platforms, including metaverses, IoT devices, smart cities, and government services. This enhances user experience, reduces risk, and allows users and service providers to access standardized, privacy-preserving authentication mechanisms across domains.
Cross-chain state verification and asset bridging support migration of both identity and digital assets, creating a future-proof, user-centric identity paradigm.

4. Applications and Benefits

4.1 Quantum-Resistant Security

All protocol operations rely on NIST-standard quantum-resistant cryptography, providing long-term resilience against quantum and classical attacks.

4.2 Privacy-by-Default

Transactions and credential operations are shielded by default using zk-SNARKs, ensuring confidentiality and supporting sector-specific privacy needs (healthcare, finance, public services).

4.3 Sustainable Scalability

PoST consensus minimizes energy use, supporting environmentally responsible, global-scale networks. Batch verification and off-chain proof computation further enhance scalability.

4.4 Unified Identity & Interoperability

UNIC-BP enables users, devices, and AI agents to port identities and credentials seamlessly across chains and platforms, reducing fragmentation and risk.

4.5 Example Use Cases

a. IoT & Smart Cities: Provides scalable, secure, and privacy-preserving authentication for billions of devices and infrastructure components.

b. Healthcare and Finance: Facilitates confidential record exchange and compliance with privacy regulations.

c. E-Government & Public Services: Supports secure citizen authentication and frictionless access to services.

d. Cross-Chain Digital Asset Transfer: Enables trustless, atomic movement of assets and credentials between legacy and next-generation blockchains.

e. AI and Autonomous Agent Authentication: Provides persistent, verifiable identities for AI agents, digital twins, and autonomous vehicles.

5. Security, Privacy, and Scalability Analysis

UNIC-BP's architecture delivers robust protection against present and future threats:

- Security: Lattice-based cryptography prevents quantum-enabled key recovery. PoST consensus resists Sybil attacks and centralization. Dynamic slashing discourages malicious behavior. Forward secrecy and threshold schemes ensure system resilience.
- Privacy: Default zk-SNARK enforcement protects transaction and credential confidentiality, supporting regulatory compliance and user sovereignty.
- Scalability: PoST and batch zk-proof verification support high throughput. Off-chain proof computation minimizes on-chain costs, enabling real-time performance for IoT, metaverse, and smart city deployments.
- Resilience & Flexibility: Layered modularity allows for seamless protocol upgrades, composability with dApps and wallets, and rapid adoption of new cryptographic advances.

DISCUSSION

UNIC-BP closes persistent gaps in blockchain and identity management by integrating quantum-resistant security, privacy-by-default, sustainable consensus, and native interoperability. Its forward-compatible, layered design enables continuous improvement and adaptation to evolving threats and application needs.

Challenges remain, including optimizing zk-SNARK generation and verification costs, broad adoption of post-quantum cryptography in hardware and SDKs, and fostering global standardization and collaboration. Real-world deployments and pilot projects in healthcare, smart infrastructure, and government will be essential for further validation and refinement.

CONCLUSION

UNIC-BP offers a blueprint for universal, privacy-preserving, and quantum-secure authentication in an increasingly interconnected world. Its modular architecture unites the latest advances in cryptography, privacy, consensus, and interoperability to create a robust foundation for digital identity and credential management.

Further research should focus on protocol optimization (e.g., zk-SNARK efficiency, PoST scalability), cross-chain frameworks, formal security proofs, and real-world pilots. Collaboration with industry, standards bodies, and open-source communities is vital for realizing the vision of secure, interoperable, and user-centric digital societies.

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ARTIFICIAL INTELLIGENCE IN TEACHING BUSINESS: OPPORTUNITIES, CHALLENGES, AND PEDAGOGICAL RESPONSES

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ABSTRACT

Artificial intelligence (AI), particularly generative AI, is rapidly reshaping how organizations and educational institutions create, manage, and evaluate business communication. This paper synthesizes recent empirical and conceptual work on the integration of AI into the workplace, evaluates implications for business executives and organizations, and proposes a course module with assignments to teach responsible and effective AI use in a college-level introduction to business class. Key findings show that AI can raise productivity and quality in customer-facing and internal communication, while simultaneously creating ethical, regulatory, and skill-development challenges for educators and managers (Brynjolfsson et al., 2025; Mayer et al., 2025). The paper concludes with implications for curriculum design and organizational policy that emphasize AI literacy, critical evaluation, ethical constraints, and empirically grounded deployment strategies.

INTRODUCTION

The acceleration of accessible generative AI tools (e.g., large language models) has disrupted established practices in business. From drafting external-facing marketing copy to aiding frontline service agents in real time, AI is enabling faster content production, personalization at scale, and data-driven communication decisions. At the same time, biases in model outputs, potential misinformation, intellectual property concerns, and shifting workplace roles pose immediate pedagogical and managerial challenges. This paper addresses the problem: How should business education and organizational practice adapt to the adoption of AI so that business executives reap its benefits while minimizing ethical, legal, and competency risks?

This work has three goals: (1) synthesize current research on AI's effects on business communication and workplace outcomes; (2) propose teaching modules and assignments that prepare students for modern communicative roles that involve AI; and (3) outline policy and curricular implications for both business schools and employers.

LITERATURE REVIEW

This section presents a very brief review of the current literature that discusses AI's impact on productivity, quality, risks, ethics, and pedagogy.

AI and Productivity in Business

Several empirical studies report productivity gains when workers use generative AI as an extra tool in the work environment. Field and experimental evidence from customer-service contexts finds increases in output per hour, improved customer satisfaction, and sometimes improved employee retention and learning when employees had access to AI help (Brynjolfsson et al., 2025). These studies suggest AI can function as an on-the-job tutor—disseminating best practices and helping less-experienced workers perform at higher levels.

Business Quality, Customization, and Risk

AI systems enable highly tailored messaging and rapid drafts, making multichannel personalization possible. Industry and academic surveys report executives increasingly adopt AI for ideation and drafting, though they often heavily edit outputs due to concerns about accuracy and brand fit (The Harris Poll et al., 2024). While quality often improves in repetitive or template-driven tasks, risks of factual inaccuracy, inconsistent tone, and legal exposures (e.g., misrepresentation, IP infringement) remain.

Ethical, Legal, and Organizational Governance

Researchers argue that the ethical implications of AI in work are challenging effects on meaningful work, transparency, bias, and accountability require deliberate frameworks (Bankins & Formosa, 2023; Maiti et al., 2025). Organizations are increasingly called upon to create policies that govern acceptable AI use and to ensure human oversight for consequential decisions. Education plays a role in preparing future managers to enforce such frameworks.

Pedagogical Approaches in Higher Education

Universities and institutions are rapidly developing guidelines and curricula for GenAI fluency (Wang et al., 2024). Approaches range from strict bans to integrated "AI-fluent" curricula that teach AI tool use, prompt literacy, fact-checking, and ethical reasoning. Early evidence suggests that guided integration—teaching students to use AI as a collaborator while maintaining critical oversight—produces better learning outcomes than outright prohibition.

PURPOSE OF THE STUDY

Business programs must reconcile two realities: (1) employers increasingly expect graduates to be AI-competent employees who can use AI tools to generate and evaluate content; and (2) the same AI tools raise ethical, legal, and quality-control issues that require managerial judgment and communication literacy. The purpose of this paper is to present an evidence-based outline for teaching an AI-aware introduction to business course and to provide concrete course content (e.g., assignments, rubrics, and learning outcomes) that prepare students both to use AI productively and to govern its use responsibly in organizations.

CONCEPTUAL FRAMEWORK

This paper uses a socio-technical framework that treats AI as both a technology and a social actor embedded in organizational processes. The framework emphasizes four interdependent competencies for business executives:

1. Prompt and tool literacy — ability to craft prompts, choose proper models, and understand tool limits.

2. Critical evaluation — capability to fact-check, edit, and confirm AI output for accuracy and brand voice.

3. Ethical and legal awareness — consideration of privacy, bias, attribution, IP, and disclosure obligations.

4. Process integration and governance — skills to design workflows where human oversight is clearly defined and quality is measurable.

Educational design should explicitly teach each competency through applied work and reflection.

METHODOLOGY

This is a conceptual and pedagogical synthesis drawing on peer-reviewed studies, white papers, industry reports, and university policy analyses published between 2020–2025. Key empirical inputs include experimental workplace studies, institutional surveys on AI adoption, and policy reviews (Brynjolfsson et al., 2025; the Harris Poll et al., 2025; Wang et al., 2024). Where empirical gaps exist, this paper integrates best-practice recommendations from practitioners and professional associations.

FINDINGS AND ANALYSIS

This findings section addresses the aforementioned benefits and issues.

AI Streamlines Routine Business Tasks and Increases Productivity

Studies consistently show generative AI helps with routine drafting, email responses, and templated communications, enabling speed and throughput gains. For example, field evaluations in customer service contexts reveal measurable increases in handled cases per hour and improvements in customer sentiment when managers used AI help (Brynjolfsson et al., 2025). However, it should be mentioned that this increase in productivity is mixed among employees with different experience levels and role types benefit unevenly.

AI Increases the Need for Human Editorial Oversight and Critical Literacy

Industry surveys show executives often use AI-generated text as a starting point and then heavily edit it to for accuracy, conciseness, completeness, and authentic voice. Frequent errors include assertions of fact without sources, subtle tone mismatches, and culturally insensitive phrasing (Getchell et al., 2022; The Harris Poll et al., 2024). Human editorial control and fact-checking skills are still critical.

Ethical and Legal Concerns Are Immediate and Practical

AI adoption raises ethical issues (e.g., bias, misinformation, surveillance, work displacement) and legal questions (e.g., IP of AI outputs, data privacy, regulatory compliance). Academicians and other scholars call for organizational policies that require disclosure of AI use in some contexts and hold humans accountable for final outputs (Bankins & Formosa, 2023; Maiti et al., 2025).

Institutional Responses Are Shifting Toward AI Fluency Rather Than Prohibition

Leading universities and professional bodies increasingly emphasize AI fluency—teaching how to use tools responsibly—rather than complete bans. Some institutions are mandating AI fluency components across curricula to prepare graduates for modern workplaces (Wang et al., 2024).

Implications of AI Use in Business Education

Course activities should instruct students when AI is helpful (e.g., first-draft generation, brainstorming, customization) and when human-authored content is preferable (e.g., high-stakes communications). Educators must build assignments requiring students to annotate edits to AI output, justify changes, and document verification steps. Syllabi must include modules on AI ethics, IP basics, and firm-level governance mechanisms (e.g., approval workflows, audit trails). Business courses should integrate AI across assignments, ensuring students show both effective use and ethical reasoning.

PEDAGOGICAL DESIGN: COURSE MODULE AND ASSIGNMENTS

Below is a proposed 15-week module titled "The Use of AI in Business" designed for an undergraduate or graduate-level business course. Learning objectives align to the four above-mentioned competencies.

Student Learning Outcomes

By the end of the module, students will be able to:

1. Demonstrate prompt-engineering skills to generate AI drafts for target audiences.
2. Critically evaluate and edit AI-generated content for factual accuracy, authentic voice, and ethical risk.
3. Apply an ethical framework to decide when and how to disclose AI assistance.
4. Design a brief organizational policy or workflow that governs AI use in business tasks.

Weekly Schedule (15 weeks)

Weeks 1-2: Introduction to AI in business (e.g., evolution, tools, uses)

Week 3-4: Prompt literacy workshop; prompt engineering (hands-on with various AI tools)

Week 5-6: Editorial practices; fact-checking; authentic voice; humanizing output

Week 7: Ethics, bias, and IP in AI-generated communication

Week 8: Integrating AI in Marketing and Public Relations; case studies

Week 9-10: AI and Business Communication; decision support; visual creation

Week 10: Using AI in Human Resources

Week 11: AI governance; policy design; approval workflows

Week 12: Capstone project work; peer reviews

Week 13: Guest lecture from an industry executive

Week 14: Capstone presentations

Week 15: Reflection, assessment, and portfolio compilation (including AI-use disclosures)

Course Assignments

The below assignments for the "AI Use in Business" course include instructions, learning outcomes, rubrics, and weightings.

Assignment 1: Prompt Engineering Lab (Individual) Weight: 10%

Students will produce three AI-generated drafts of a single business email (e.g., a customer apology, an internal announcement, and a sales outreach), each using a different prompting strategy (i.e., concise prompt, role-based prompt, multi-step prompt). Students must include the prompts used, the outputs, and a 500-word analysis of why outputs differed and which prompt generated the best result for the intended audience.

Learning outcomes: prompt literacy, understanding relationship between prompt design and output quality

Rubric criteria: clarity of experimental design (20%), quality of prompts (30%), depth of analysis and justification (30%), grammar and presentation (20%)

Assignment 2: AI Editing and Fact-Check (Pairs) Weight: 20%

Students receive an AI-generated press release containing three intentionally embedded inaccuracies and one tone mismatch. Pairs must (a) find and correct factual errors with citations, (b) edit to restore authentic brand voice, and (c) write a one-page audit log describing each edit and verification step.

Learning outcomes: editorial oversight, fact-checking, written documentation, and transparency

Rubric criteria: accuracy of corrections (40%), quality of edits (30%), documentation clarity (20%), citation quality (10%)

Assignment 3: Ethics Case Brief (Individual) Weight: 15%

Students analyze a case where an AI-generated message caused reputational harm (professor can provide a fictionalized case reflecting real incidents). Students produce a 1,500-word paper that: (a) identifies ethical breaches, (b) explains causes, (c) proposes mitigation measures, and (d) recommends disclosure language for future AI-assisted content.

Learning outcomes: ethical reasoning; policy recommendation; persuasive writing

Rubric criteria: problem identification (25%), ethical analysis (30%), practicality of recommendations (30%), writing quality (15%)

Assignment 4: Organizational AI Communication Policy (Group Capstone) Weight: 35%

Groups (3–4 students) design a one-page AI organizations policy and a 10-slide executive presentation for senior leaders arguing for adoption of AI. Policy must include permissible use cases, approval workflow, auditing approach, and disclosure guidelines. The presentation must include a brief pilot plan and key performance indicators to evaluate the pilot. Students submit the policy, a 500-word rationale, and deliver a 10-minute presentation.

Learning outcomes: governance, strategic communication, evaluation metrics

Rubric criteria: policy completeness and clarity (40%), feasibility and governance (30%), pilot metrics and evaluation (20%), presentation quality (10%)

Assignment 5: Reflection Portfolio (Individual) Weight: 10%

Students compile a portfolio showing drafts and final versions of work where AI was used, along with a reflective essay (750 words) describing their evolving approach to AI use and ethical decision-making. Portfolios serve as artifacts for job interviews and professional development.

Learning outcomes: reflective practice; documentation and transparency

Rubric criteria: completeness (30%), depth of reflection (40%), articulation of growth (30%)

DISCUSSION: INTEGRATING RESEARCH INTO TEACHING

The assignment set is intentionally scaffolded—from prompt experimentation to governance—so students see a lifecycle: generate, evaluate, decide, and deploy. It reflects empirical findings showing that AI helps productivity but requires editorial oversight (Brynjolfsson et al., 2025; The Harris Poll et al., 2024). Embedding audits and disclosure into coursework familiarizes students with the documentation employers increasingly expect.

Courses should also teach assessment metrics for evaluating AI-assisted business tasks (e.g., response rate, customer satisfaction, error rate, audit exceptions), drawing from workplace studies that link AI assistance to measurable outcomes. Educators can partner with organizations for capstone pilots to give students real-world experience and produce publishable evaluation data.

IMPLICATIONS FOR BUSINESS AND EDUCATION

Implications of using AI exist for business in practice and policy and for education concerning curriculum and pedagogy.

Business Implications

1. Adopt AI as a support tool, not a replacement for people. Evidence shows gains when AI supports human judgment rather than replaces it. Implement approval and audit mechanisms.

2. Measure impact and heterogeneity. Productivity gains are not uniform; track who benefits and why. Use metrics that capture quality, not only quantity.

3. Require disclosure in sensitive contexts. For legal and trust reasons, disclosing AI help in customer-facing materials where necessary. Establish IP and usage policies.

Education Implications

1. Teach prompt literacy and editing as core skills. Prompting is now an applied communication skill—courses should include labs and portfolios.

2. Make ethics and governance integral, not optional. Case-based learning on ethical failures improves anticipatory reasoning.

3. Partner with industry for pilots and guest input. Capstones that involve company pilots help students learn measurement and change communication.

LIMITATIONS AND FUTURE RESEARCH

This paper synthesizes diverse, albeit brief, recent literature but does not present new empirical data collected by the author. Several open questions merit empirical study: (a) long-term effects of AI on employees' skill development and career trajectories; (b) cross-cultural variance in AI acceptance for external communications; (c) optimal governance structures in different organizational sizes and industries. Longitudinal studies and randomized field experiments in varied organizational contexts would strengthen evidence-based recommendations.

SUMMARY AND CONCLUSION

AI is transforming business tasks—enabling scale, speed, and personalization, while introducing new ethical and governance challenges. Educators and organizations should treat AI as a socio-technical phenomenon: teach the craft of prompt and editorial literacy, instill ethical and legal prudence, and design governance structures that preserve human accountability. The assignments and module proposed here operationalize these principles in a pedagogically coherent sequence from hands-on experimentation to policy design. Implementation of such curricula will better prepare graduates for an AI-augmented workplace and help organizations realize AI's potential while managing its risks.

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AI TRANSFORMATION IN ENTERPRISES: A GENERAL ROADMAP AND BALANCED EVALUATION FRAMEWORK

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ABSTRACT

Due to the rapid evolution of the artificial intelligence industry, the proliferation of products, and the misuse of terminology, it has become difficult for business decision-makers to make sound investment choices regarding the need for AI Agents. This is particularly true for small and mid-sized companies where such investments can be very labor-intensive and must overcome significant cost hurdles. Firms which do not possess the specialized human capital necessary to evaluate these systems within the context of their operations commonly experience resource misallocations of resources due to failed AI projects. This paper provides an evaluation framework to help managers make sound choices with respect to investment in AI Agent deployment. At the macro-organizational level, the authors outline three domains of evaluation: Instructions, Knowledge/Actions, and Integration into current systems. At the micro-organizational level, the authors introduce a balanced evaluation approach to assess the success of such deployments in practice, incorporating not only technical metrics but also human-centered, temporal, and contextual dimensions. Sample implementation data are presented and analyzed to illustrate deployment typical costs of the proposed approach relative to full-scall implementation of commercial turnkey options.

KEYWORDS: artificial intelligence, AI agents, large language models, system evaluation, investment

BACKGROUND AND LITERATURE

AI agents represent a significant milestone in the development of artificial intelligence. Agents, can collaborate with complex environments with minimal human intervention empowered by LLMs. (Hughes et al., 2025). The understanding of the components of an AI agent may differ depending on the application scenario. For example, in the health care filed, Medical AI agents consist of four core components—*planning* (integrating symptoms and test results to generate diagnoses), *action* (controlling surgical robots or generating reports), *reflection* (detecting abnormalities in imaging or monitoring vital signs), and *memory* (recording medication administration and patient history)—which collectively enable intelligent decision-making and adaptive evolution in complex healthcare environments. (Liu et al., 2025). In the field of chemistry, Ramos et al. (2025) conducted a comprehensive review on LLM-based autonomous agents. They pointed out that there is currently no unified terminology for discussing the concept of "agents." For example, Gao et al. (2024) proposed a hierarchical framework from the perspective of autonomy, emphasizing the differences in agents' decision-making and reasoning capabilities while Wang et al. (2024) adopted a functional-structure approach, dividing agents into four modules: profiling, memory, planning, and action. Weng (2023) also identified four elements—memory, planning, action, and tools—while Xi et al. (2025) viewed agents from an architectural perspective, abstracting them into a system composed of a brain, perception, and action, in which the brain is typically powered by an LLM. Given the variety of terminology associated with such different perspectives, it has become difficult for decision-makers to make sound investment choices regarding the need for AI Agents.

Compared with large firms, SMEs often encounter limitations stemming from restricted human and financial resources (Dörr et al., 2023). For SMEs technological investment is often motivated by a desire to generate a notably high return on investment (ROI) as these firms are constrained by limited manpower and capital. Given the technological disparities, the gap between large corporations and SMEs may place the latter at a significant disadvantage (Nagy et al., 2023). In this context, SMEs increasingly regard AI as a critical element for transforming their current conditions. Consequently, they must carefully navigate the adoption of innovative and disruptive technologies due to the profound impact such changes can exert on their organizational and environmental dynamics (Khan et al., 2021). Building upon these circumstances, this study proposes an agent deployment framework grounded in enterprise practice. The aim is to move beyond the overly complex and abstract notions of agents by introducing a cloud-based**,** SME-oriented roadmap for agent deployment**—**progressing from different modules levels through minimally feasible agent modules **to** maximize business value while minimizing unnecessary investment**.**

At the same time, we observe that the application of agents often suffers from failures in human-centered experience and contextual alignment, which ultimately lead to business losses. Meimandi et al. (2025) summarized several failure cases across healthcare, financial services, and retail sectors, and proposed four core evaluation dimensions**—t***echnical, human-centered, temporal, and contextual*—to assess and validate the success of agent systems. Building on these dimensions, we propose a user-oriented approach to evaluation designed to help SMEs determine whether their agent-based projects have achieved successful outcomes.

METHODOLOGICAL FRAMEWORK

This article employs the Technology, Organization, and Environment (TOE) framework to clarify the rationale behind the three-phase process of AI adoption: instructions, knowledge/actions, and integration. Originally introduced in "The Processes of Technological Innovation" (DePietro et al., 1990), the TOE framework examines how technological organizational, and environmental factors collectively influence the adoption of technology within enterprises. While the TOE model was developed for general decision-making within SMEs, the application of the TOE perspective provides a structured approach for understanding AI deployment. To ensure that AI projects are successfully implemented, this article also introduces a complementary and balanced, human-centered evaluation framework. This framework enables the assessment of practical outcomes at both the individual and task levels, supporting sustainable and effective integration of AI technologies.

TOE Contexts and Their Influence

The *technological context* encompasses all internal and external technological factors relevant to the enterprise. The internal factors include the foundational infrastructure characteristics and capabilities that dictate the feasibility, speed, and cost of adopting new technologies. The external factors include the availability and ability to implement innovations—whether incremental, integrative, or disruptive—that offer the enterprise pathways for transformation and growth. Together, these considerations form the technological landscape in which adoption decisions must be made.

The *organizational context* includes the enterprise's internal structure, resources, processes, and management mechanisms. Factors such as organizational structure, interdepartmental connections, communication channels, support from top management, resource flexibility, and company size are all influential in determining the organization's readiness and approach to adopting new technologies.

The *environmental context* refers to external factors such as industry structure, lifecycle, support infrastructure, and regulatory environment. This context describes the competitive landscape, technological support ecosystem, and governmental regulations that shape, drive, or constrain the enterprise's technology adoption behaviors.

Phased AI Adoption Shaped by TOE Constraints

Enterprises do not adopt AI simply due to readiness; rather, the constraints posed by the three TOE contexts necessitate a phased, progressive approach. AI deployment typically evolves through three stages—each shaped by technological, organizational, and environmental limitations. The degree and nature of these constraints vary by phase, guiding organizations from simpler to more complex implementations. Generally, organizations begin with instruction-based AI, which faces minimal constraints. They then advance to knowledge/action-based AI, requiring enhanced organizational capabilities, and finally achieve full integration, which demands the highest levels of technological maturity, organizational coordination, and environmental alignment.

Three Stages of AI Agent Deployment

Stage 1: Instructions (Instruction Phase). In the initial phase, the constructed AI Agent utilizes pre-prompts that include an overview of the enterprise, specific tasks to be completed, and detailed instructions. This configuration enables the automation of simple tasks, such as information extraction and repetitive analysis. However, at this stage, the Agent does not leverage enterprise-specific knowledge, such as product information, HR policies, organizational vision, internal procedures, or training content for new employees. From the perspective of the TOE framework, this phase emerges because technological, organizational, and environmental constraints are at their lowest intensity.

Technologically**,** most small and medium-sized enterprises possess only basic IT resources, such as a company website, lightweight databases, or limited software development capabilities. Pre-prompted agents can operate through simple API calls without requiring system-level integration, high-quality internal data, or mature infrastructure. For example, for customer support sentiment scoring, a firm may simply pass each chat log or conversation transcript to a generative AI model to obtain a sentiment assessment. This allows the customer support department to gain immediate feedback without manually reviewing historical communications—a task that would otherwise require substantial time investment from support managers. Such instruction-based agents represent a form of incremental innovation, imposing minimal disruption and posing low technological risk to the enterprise but higher possibility to accept this innovation.

Organizationally**,** instruction-based agents allow firms to identify promising AI use cases before committing significant resources or undertaking structural changes. Because these tasks are highly automatable and isolated from core workflows, they do not require cross-functional coordination, workflow redesign, or extensive employee training. Continuing the sentiment scoring example, managers can easily evaluate the benefit of AI-powered insights without altering existing processes or reallocating staff. This low barrier to experimentation makes it easier to gain top management support and creates organizational momentum for further AI adoption.

Environmentally, firms face limited regulatory, competitive, or ecosystem-driven pressures at this stage. Instruction-based agents do not require compliance mechanisms, industry-standard data interfaces, or connections to external partners. As a result, organizations can experiment freely without concerns about privacy audits, interoperability requirements, or regulatory scrutiny. Consequently, the instruction phase reflects a **low-constraint equilibrium,** where firms can explore AI adoption with minimal risk and minimal dependence on technological, organizational, or environmental readiness.

Stage 2: Knowledge and Actions. At the next stage, the Agent is enhanced with a dedicated enterprise knowledge base. This advancement enables the Agent to deliver personalized responses tailored to the organization's unique needs and to integrate with other key systems, such as internal ERP and CRM systems. The Agent's capabilities expand beyond basic automation, supporting more complex and business-specific functions, including multi-step workflows, contextual recommendations, and domain-aware reasoning. From the perspective of the TOE framework, this phase emerges because technological, organizational, and environmental constraints begin to intensify relative to the instruction phase.

Technologically, a knowledge-enabled agent requires more mature internal data resources, stable system interfaces, and improved infrastructure reliability. Firms must curate their product information, HR documents, policy manuals, FAQs, and historical records into structured or semi-structured formats. Additionally, integrating the Agent with ERP or CRM systems necessitates APIs, identity management, and secure data access protocols—capabilities that exceed the minimal requirements of prompt-based usage. From the perspective of external technological innovation, this stage reflects what Tushman and Nadler (1986) classify as synthetic innovation—where existing technologies are recombined in new ways to create higher-value applications. Rather than relying on entirely new technological breakthroughs, firms leverage their existing ERP or CRM APIs and connect them to the AI Agent to unlock new use cases. For example, a customer-behavior analysis agent may combine internal sales data with information about competitors' products to identify customers with diverse purchasing preferences. Once such customers are detected, the Agent can automatically label them through CRM APIs and trigger personalized marketing actions. This recombination of existing systems and AI capabilities illustrates how synthetic innovation enables firms to expand their operational possibilities without requiring radical infrastructure changes.

Organizationally, the transition to this phase requires stronger cross-functional coordination and clearer governance mechanisms. Knowledge-base construction involves multiple departments (e.g., HR, product, customer support), necessitating shared standards for documentation, terminology, data ownership, and content updates. Workflow-level actions also require employees to trust AI outputs and adjust their day-to-day practices. Top management support becomes increasingly critical as the scope of AI involvement expands from isolated tasks to core business processes. This stage also introduces the need for role definitions (e.g., AI administrators, reviewers, auditors) that did not exist in the instruction phase.

Environmentally, firms begin to encounter moderate external pressures and emerging constraints during Stage 2. Competitors may be adopting enterprise-embedded AI, customers may expect personalized responses or automated follow-ups, and partners may start requesting standardized data interfaces. Regulatory considerations—such as data privacy, auditability, or logging requirements—also become more salient when AI interacts with sensitive customer or employee information. Although these pressures are not yet overwhelming, they signal the need for greater alignment with industry norms and compliance expectations. Consequently, the knowledge-and-actions phase represents a medium-constraint configuration**,** in which firms move beyond low-risk experimentation toward structured, workflow-level AI deployment—requiring increased technological sophistication, greater organizational coordination, and heightened environmental awareness.

Stage 3: Integration Phase. In the final stage, the Agent becomes fully integrated into the daily work environments of employees. For example, it may be embedded within collaborative platforms such as Microsoft Teams, enabling employees to interact with the Agent as a virtual colleague rather than as a separate tool. At this level of maturity, the Agent is woven into enterprise-wide processes and systems, facilitating seamless collaboration, workflow orchestration, and end-to-end optimization across the organization. From the perspective of the TOE framework, this phase emerges because technological, organizational, and environmental constraints reach their highest intensity, making deep integration both necessary and feasible.

Technologically**,** system-level integration requires advanced infrastructure maturity. The Agent must interact reliably with multiple enterprise systems—ERP, CRM, supply chain management tools, knowledge management systems, communication platforms, and identity-management frameworks—through secure APIs and unified data pipelines. The underlying data must be high quality, consistently governed, and accessible through standardized schemas. Firms must also implement agent monitoring, logging, auditing, model version management, and automated fail-safes to ensure safe and consistent operation. At this stage, external technological innovation aligns with what Tushman and Nadler (1986) characterize as discontinuous (or radical) innovation. Unlike synthetic innovation, which recombines existing technologies, deep integration requires architectural transformation: legacy systems must be reconfigured to interact with AI; workflows must be re-engineered; and digital infrastructures must support continuous, autonomous machine-driven actions. The shift from tool-level AI to system-level AI represents a break from existing technological routines and constitutes a high-impact transformation across the enterprise.

Organizationally, this phase demands enterprise-wide coordination and significant structural change. AI integration alters workflows, job roles, responsibilities, and governance mechanisms.

Employees must collaborate with the Agent in real time, requiring new forms of human–AI teamwork and process redesign. Formal AI governance frameworks must be institutionalized—covering accountability, risk management, compliance, model oversight, update cycles, and ethical guidelines. Leadership commitment becomes essential, as integrating AI into core operations requires substantial investment, cross-functional alignment, and cultural acceptance. The organization must evolve from isolated AI experimentation to a state in which AI is embedded in its routines, standard operating procedures, and strategic priorities.

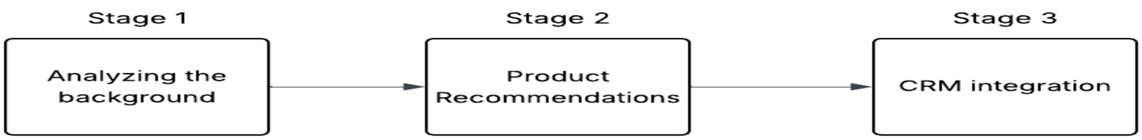
Environmentally, firms at this stage confront the strongest external pressures. Competitive forces increasingly reward firms that achieve higher degrees of automation, personalization, and operational efficiency through AI. Customers and partners expect AI-enabled interactions, real-time coordination, and standardized interfaces for data exchange. Regulatory requirements—especially regarding transparency, security, explainability, and auditability—become mandatory rather than optional. Furthermore, firms must align with industry ecosystems that are rapidly standardizing AI communication protocols, interoperability layers, and compliance norms. Failure to integrate AI deeply may result in competitive disadvantages or inability to interoperate with supply chain partners. Consequently, the integration phase represents a high-constraint configuration**,** where AI becomes a foundational component of enterprise systems and workflows. Firms transition from using AI as a supportive tool to embedding it as a core operational capability—achieving full organizational transformation driven by mature technology, institutionalized structures, and strong environmental pressures.

IMPLEMENTATION COSTS

Currently, the major cloud service providers in the United States include Microsoft Azure, Google Cloud, and Amazon AWS. Based on the three phases of deployment described above, costs increase progressively as firms advance through each stage, since more cloud computing services and integrations are required. However, the advantage of this phased approach is that organizations avoid jumping directly to Stage 3 without first validating AI Agent use cases in the earlier phases—thereby preventing unnecessary organizational transformation and costly investment waste.

Many external AI development companies at present tend to sell a single AI product yet deploying AI agent-based solutions often require enterprises to reinvest in instructions, actions, and knowledge components. The performance shown in provider demos frequently diverges from the results obtained after real deployment, leading to sunk costs and disappointing outcomes. Using Microsoft Azure as the reference platform, we compare the costs associated with each of the three deployment stages. In this section, a detailed example is developed to compare the costs of each implementation stage and contrast the overall cost with that of a typical turnkey implementation that immediately advances to Stage 3 as described above.
As an example, consider how a sales team benefits by providing specific and personalized recommendations when customers request a quote. This requires sales representatives to understand each customer's background, have strong product knowledge, and be able to quickly access relevant information within their daily workflow. According to the 3 stages of implementation theory provided above, the implementation is shown in Figure 1.

Figure 1. Three Stages of Implementation



Stage 1: This stage involves analyzing background data—such as company size, location, and prior purchasing activity—to generate contextual insights for sales representatives. The goal is to support informed decision-making before any recommendations are made. All required data is assumed to be readily available.

Stage 2: Using Retrieval-Augmented Generation (RAG), the system leverages a curated product knowledge base to generate personalized product suggestions for sales representatives based on the customer's profile. This stage establishes the core recommendation logic.

Stage 3: In this phase, the system is integrated into the enterprise's CRM (e.g., Salesforce, Dynamics 365), enabling automatic background insights based on past interactions with customers and enabling product recommendations to appear within the sales workflow—such as when a new contact is added or revisited.

Cost Component Definitions

Costs are categorized into the three dimensions of the TOE framework, differentiating between direct computational expenses, internal human capital adjustments, and external market-driven fees.

Table 1. Cost Categories

Category	Cost Component	Description
Technology (T)	Inference Costs (Token Usage)	Variable costs for LLM processing based on token volume. Pricing reflects standard consumption-based tier.
	Infrastructure & Knowledge Base	Hosting of application logic, vector databases, logging services to support RAG. Scales with architecture complexity.
	Development Labor	Labor for agent configuration, integration, and prompt engineering.
Organization (O)	Internal Labor	Cost of reallocating internal staff (e.g., IT, analysts) from their core duties.

	Training & Change Management	Upskilling employees, workflow redesign, and adoption efforts.
	Testing & Governance	Quality assurance, red-teaming, governance protocols.
Environment (E)	Compliance & Security	Fees for regulatory audits, security assessments, and automation tools.
	Risk & Consulting	Strategic consulting (e.g., AI governance, legal, architecture). Typically billed hourly.

Technology (T): Computational & Infrastructure Costs

Technological costs are conceptualized using consumption-based ("pay-as-you-go") cloud service models, reflecting the scalability needs of SMEs. Data is derived from current pricing structures of major providers; Microsoft Azure (2026), Google Cloud (2026), and Amazon Web Services (2026). Additional implementation costs include the price of specialized human capital, often in the form IT consultants. (Note that all of the national wages referenced in the example below can be found through the web services and published data of the United States Bureau of Labor Statistics (2026).)

- **Inference Costs (Token Usage):** Represents the variable expenditure for LLM processing. Inference costs scale with interaction frequency and workflow complexity and are measured by the volume of input and output tokens consumed during agent reasoning. Pricing data were collected from the Global Standard (consumption-based) service tier of major cloud service providers and are normalized to U.S. dollars per one million tokens for comparability. Note that all three major providers share the same pricing structure which indicative of the current oligopolistic structure of the cloud computing industry in the United States.

Table 2. Inference Costs

Cloud Provider	Input Tokens	Output Tokens
Microsoft Azure	$3.00	$15.00
Google Cloud	$3.00	$15.00
Amazon AWS	$3.00	$15.00

- **Infrastructure & Knowledge Base:** The cost category captures the costs associated with hosting application logic and enabling Retrieval-Augmented Generation (RAG) capabilities, including vector-based knowledge stores, application hosting environments, and logging mechanisms required for observability and auditability. Although pricing models and billing mechanisms differ across cloud service providers, these costs generally scale with system usage and architectural complexity. Azure AI Search pricing is the representative benchmark used to illustrate how infrastructure and knowledge base costs evolve across deployment stages, increasing in tandem with deeper system integration and higher operational maturity of AI Agents.

Table 3. Infrastructure and Knowledge Base Costs

Azure	Free	Basic	S1	S2	S3	L1	L2
Storage	50 MB	15 GB	160 GB	512 GB	1 TB	2 TB	4 TB
indexes/ service	3	15	50	200	200	10	10
Price per Search unit	$0/month	$73.73/ month	$245.28/ month	$981.12/ month	$1,962.24/ month	$2,802.47/ month	$5,604.21/ month

- **Development Labor:** Quantifies the technical effort to configure and integrate agents. As cloud providers do not publish labor rates, this component can be estimated using BLS SOC code 15-1252 (Software Developers), with a median hourly wage of $63.98 to approximate implementation costs.

Organization (O): Human Capital & Process Costs

Organizational costs reflect the internal effort required to adopt AI, focusing on workforce allocation and governance rather than software purchases.

- **Internal Labor (Opportunity Cost):** Measures the cost of reallocating existing staff (IT administrators, domain experts) from regular duties to AI oversight. To value this strategic work accurately, costs were benchmarked against BLS SOC code 13-1111 (Management Analysts) at a median hourly rate of $48.33.

- **Training & Change Management:** Encompasses resources for upskilling employees and redesigning workflows to accommodate AI collaboration. These costs were modeled using BLS SOC code 13-1151 (Training and Development Specialists) at a median hourly rate of $32.46.
- **Testing & Governance:** Accounts for quality assurance, "red-teaming" (safety testing), and establishing accountability protocols. As agent autonomy increases, governance costs were calculated using BLS SOC code 15-1253 (Software Quality Assurance Analysts) at a median hourly rate of $48.96.

Environment (E): Compliance & Strategic Costs

Environmental costs capture externally imposed requirements. Unlike internal organizational costs, these costs must be estimated from local market-rate professional service fees to reflect the prevailing regulatory environment and labor market conditions faced by the enterprise at its geographic location(s) rather than using national wage data.

- **Compliance & Security**: Represents expenditures for meeting regulatory obligations (e.g., GDPR, SOC 2). Estimates include fees for third-party audits and subscription costs for compliance automation platforms (e.g., Vanta, Drata).

- **Risk & Consulting:** Accounts for external advisory services to mitigate legal and operational risks. Costs must be based on the prevailing market rates for specialized technology counsel and AI strategic consultants.

ANALYSIS

Following the collection of cost and implementation data based on the framework proposed in this paper, a systematic comparison is performed between the customized, phased deployment approach and commercially available turnkey ("buy") solutions offered in the market. This example excludes token usage, infrastructure, and compliance costs from comparative analysis. These components are classified as ongoing operational expenses and are largely unavoidable whether a firm chooses to build in-house or purchase a third-party solution. Instead, the focus is placed on labor-related implementation costs.

Table 4. AI Agent Costs by Implementation Stage and Cost Category

Stakeholder Role	Rate	Stage 1	Stage 2	Stage 3	Total Hours
Software Developers	$63.98	15–25 hrs	120–180 hrs	300–450 hrs	435–655 hrs
Management Analysts (Internal Labor)	$48.33	25–40 hrs	80–120 hrs	200–300 hrs	305–460 hrs
Training & Development Specialists	$32.46	10–15 hrs	30–50 hrs	80–120 hrs	120–185 hrs
Software QA Analysts (Testing/Governance)	$48.96	10–20 hrs	60–100 hrs	150–250 hrs	220–370 hrs
Total Cost		$2,982 – $4,999	$15,455 – $23,835	$38,801 – $59,425	$57,238 – $88,259

By adopting a phased, self-developed AI agent approach, the enterprise retains full control over its software architecture and underlying knowledge assets. In particular, the enterprise knowledge base constructed during the development process is not limited to a single application scenario but remains reusable and transferable across multiple AI-enabled use cases. For example, the same knowledge base can be leveraged to support website-based intelligent customer service for product inquiries or to assist in the automated drafting of product-related sections in Requests for Proposal (RFPs). This reusability enables firms to achieve cumulative cost savings and accelerated development in subsequent AI initiatives, as new applications can be built upon existing knowledge infrastructure rather than requiring redundant data preparation and system redesign. Consequently, the benefits of the proposed approach extend beyond a single deployment, reinforcing long-term scalability and strategic flexibility in enterprise AI transformation.

Based on publicly available sources (Appinventiv, 2026; Microsoft, 2026; and Sharma, 2025), turnkey AI product solutions for SMEs typically range from $25,000 to $150,000. (Note that this range exceeds the estimated partial overall costs across the three phases shown in Table 4.) However, these commercial offerings are often narrowly scoped—designed to solve a specific function—and lack the extensibility needed for broader AI transformation within SMEs . This limited flexibility can lead to strategic hesitation, as firms may question whether investing in a one-size-fits-all solution restricts future innovation. In contrast, in-house development enables tighter alignment with business goals and greater reusability of system components. For instance, a knowledge base built for product recommendation use cases can be repurposed to power intelligent customer service agents or automate responses in RFP documentation, yielding compounding returns on initial development investment.

Moreover, the proposed phased development strategy introduces strategic checkpoints across the three stages, allowing organizations to exit early when critical feasibility issues arise. Table 5 reports possible failure points within an AI agent deployment across the various proposed stages of implementation. For example, Stage 1 may reveal that prompts return irrelevant insights due to low-quality customer data. Stage 2 might expose that unstructured product documents are incompatible with retrieval-based architecture. Stage 3 could show that sales representatives reject the tool due to workflow misalignment or lack of trust. Identifying such failures before full deployment helps avoid sunk costs and ensures that only well-aligned AI applications proceed.

Table 5. Potential Failure Scenarios by Stage of Implementation

Stage	Potential Failure Scenario	Rationale for Exit
1	Prompts fail to deliver relevant or trustworthy outputs due to unclear instructions or limited customer data.	Early prompt testing shows poor personalization, indicating limited value of continuing.
	Customer segmentation logic lacks accuracy or fails to differentiate buyer needs.	Data foundations are too weak for meaningful insight generation.
2	Product documents are poorly structured or lack metadata, making them unsuitable for embedding.	RAG pipeline returns incorrect or irrelevant product matches.

	Embeddings generate high similarity scores for dissimilar products.	Retrieval quality is insufficient to ensure accurate recommendations.
3	System doesn't align with how sales representatives actually work; adds complexity to quoting process.	Negative user feedback and poor adoption indicate misfit.
	Integration introduces instability in CRM or duplicates existing features.	Technical integration cost outweighs functional gain.

CONCLUSIONS

The advent of artificial intelligence and AI agents has disrupted the business landscape globally. The disruptive nature of this technology has left many small and mid-size firms at a disadvantage relative to larger firms due to uncertainties in how to evaluate the potential costs and benefits. Both the human capital and financial costs also impose significant barriers to the adoption of AI agents by managers unfamiliar with the technology. By applying the established and widely accepted practices of evaluating technological investments using the TOE approach to AI agents, we argue that a phased adoption of AI agents by smaller firms offers the opportunity for such enterprises to gain the necessary experience while minimizing the upfront costs of implementation. The phased approach also allows managers to identify possible points of failure where their existing systems may not be "AI-ready" or where AI agents may not be the right tool for their specific business processes and practices. We have illustrated this approach with an example using publicly available price data published by the major AI cloud computing platform providers and representative wage data.

As artificial intelligence continues to evolve, all firms, regardless of size, will need to adapt to the changing landscape. This paper has attempted to illustrate that the application of tried and true managerial approaches can be successfully adapted by managers who are willing to take a systematic approach to the problem.

Most companies' situations vary based on the resources they have; some may already have existing ERP or CRM systems. These often include some AI add-on functionalities. Investing in AI through third-party platforms like these may lower costs, but the functionalities can be limited. For example, Agentforce is an agent product from Salesforce that can connect to its Data Cloud to query product information. This platform is primarily designed for sales, marketing, or customer support teams since it is a CRM system, so the product design team might not benefit from it.

Since these situations differ, most companies provide quotes for their services, making pricing information less transparent. It is also difficult to find a unified price standard for different companies. One future research interest would be to create a company field study dataset and classify real companies into different categories based on their existing IT infrastructures, then compare the costs for similar solutions along with the three-phased AI adoption roadmap.

In addition to the future research interest, another point raised is that when a company has a clear problem to solve, it seeks a solution—whether it is an AI solution or a traditional technology solution—as long as the problem can be resolved. This article places greater emphasis on small and medium-sized companies, which often hear about AI but frequently wonder what AI can do in their organization. In this sense, it serves as an exploratory roadmap for companies to discover the benefits of AI, starting with instructions, moving to knowledge/actions, and then integration if they see tangible advantages. Companies can exit at any stage of these phases. Is there a better way to quantitatively prove that this roadmap is superior to others?

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**JUST WHAT IS THE MEASURE OF SUCCESS?
A PLURALISTIC STAKEHOLDER-CENTRIC STUDY OF SYSTEM IMPLEMENTATION SUCCESS
IN ACADEMIC INFORMATION SYSTEMS**

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There are many measures of success; in perhaps the most influential on systems success in the Information Systems field, DeLone & McLean (1992) identify six dimensions in their landmark IS Success model. Petter, DeLone, & McLean (2013) extended the model, and continued research has shown that different organizational constituents also have varying perceptions of systems implementation success (Avgerou & McGrath, 2007). Divergent sociotechnical expectations could also come into play (Avgerou & McGrath, 2007); for example, technical staff could be more focused on IS Success constructs like **System Quality**, which could be viewed through a more technical lens, whereas end users' primary concern could be **User Satisfaction**, **Individual Impact** or **Organizational Impact**, which could be more social in nature. The stakeholder role, therefore, bears further examination.

The purpose of this early-stage research is to examine the plurality of system success through the theoretical lens of stakeholder theory (Freeman, 2010), and in the context of academic information systems, specifically Enterprise Resource Planner (ERP) and Learning Management System (LMS) implementations. *User* from the IS Success model can be extended to *Stakeholder*, where the stakeholders are the system implementors (technical staff, functional leads, and superusers), end users (faculty and students), and administrators (who approve and fund the implementations). Academic systems not only afford a convenient and familiar domain for academic researchers, but also have not been widely studied with respect to the IS Success model. For this research, case studies of at least two ERP implementations and two LMS implementations will be conducted. A grounded theory methodology (Glaser, 1978) will be employed.

Each stakeholder group could have very different views of system success – i.e., budgetary shortfalls might mean failure to administrators but nothing to end users – but even within groups, faculty could diverge from students, as could technical staff from functional leads. In this early-days research, the data could take the researcher in many directions, with quantitative survey work possibly following this qualitative analysis to operationalize and further investigate the constructs that emerge here. If success is indeed viewed differently among the groups, those differences should be considered to achieve a more comprehensive result for system success; if not, there will nevertheless be theoretical insight to gain from the extension of the definition of system success to include the stakeholder.

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ARTIFICIAL INTELLIGENCE AND CONSUMER DECISION-MAKING: A SYNTHESIS OF LEARNING THEORY AND THE FIVE-STAGE PURCHASE PROCESS

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ABSTRACT

This paper synthesizes existing peer-reviewed research to examine how artificial intelligence (AI) is transforming the traditional five-step consumer decision-making process: (1) problem recognition, (2) information search, (3) evaluation of alternatives, (4) purchase decision, and (5) post-purchase behavior. Drawing on behavioral, cognitive, and social learning theories, this study analyzes the mechanisms through which AI influences consumer cognition, affect, and behavior at each stage. The integration of AI-driven technologies—such as predictive analytics, recommender systems, conversational agents, and algorithmic personalization—has shifted decision-making from a predominantly human-centered process to a hybrid human–machine interaction. Findings suggest that AI's personalization capabilities enhance relevance and reduce decision fatigue, yet also raise ethical concerns related to autonomy, privacy, and potential manipulation. This review offers a conceptual framework for understanding AI's role in shaping consumer decisions, identifies gaps in the literature, and outlines implications for marketers, policymakers, and future research.

KEYWORDS: artificial intelligence, consumer decision-making, learning theory, recommender systems, personalization, consumer behavior

INTRODUCTION

The five-stage consumer decision-making model has remained the foundation for consumer behavior research since it was first identified in 1910 by John Dewey (Bruner & Pomazal, 1988). This model consists of problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior. To date, this model represents a cornerstone framework in marketing scholarship (Kotler & Keller, 2016). Since its early conceptualization in consumer psychology research, this sequential model has provided a structured approach to understanding how individuals identify needs, acquire and process information, select among options, and evaluate outcomes. The framework has demonstrated remarkable resilience while adapting to technological, psychological, and cultural shifts in consumer markets.

The emergence of artificial intelligence as a pervasive force in commerce has introduced fundamental changes to each stage of this decision-making process. Contemporary AI technologies, including generative content systems, recommendation algorithms, predictive analytics, and virtual assistants, shape both the substance and process of consumer choice (Kietzmann et al., 2018; Kumar et al., 2021). These systems influence not merely which products consumers select but have fundamentally changed the cognitive pathways through which decisions emerge. From the initial surfacing of underlying needs through personalized suggestions to post-purchase engagement via automated feedback systems, AI intervenes in an increasing proportion of the consumer journey.

The rapid integration of AI into consumer-facing applications has generated growing scholarly interest. Research indicates that approximately 60% of consumers utilize AI tools in some capacity during their shopping decisions, with many expressing trust in algorithmic recommendations comparable to or exceeding trust in peer suggestions (Mackey, 2025). This widespread adoption necessitates a rigorous theoretical examination of how AI reshapes each phase of the decision-making process and what implications arise for consumer autonomy, decision quality, and long-term behavior patterns.

This study synthesizes empirical research and theoretical frameworks to examine how AI integration transforms consumer decision-making processes. This review shows how AI reshapes the cognitive, emotional, and social sides of consumer behavior by tracing its role across the five decision stages and linking it to established learning theories. The analysis extends beyond mere description of AI applications to explore underlying psychological processes and theoretical implications for understanding human-machine collaborative decision-making. Three research questions guide this synthesis: (1) How do AI technologies influence each stage of the consumer decision-making process? (2) What learning theory mechanisms explain these AI-mediated influences? (3) What are the ethical implications and boundary conditions of AI-driven consumer engagement?

THEORETICAL FRAMEWORK

Understanding AI's influence on consumer decision-making requires integration of multiple theoretical perspectives that illuminate different facets of the human-AI interaction. This framework synthesizes behavioral learning theory, cognitive learning theory, and social learning theory with contemporary models of technology acceptance and environmental psychology to create a comprehensive lens for examining how AI systems transform consumer cognition and behavior. This multi-theoretical approach is necessary because AI interventions operate simultaneously across multiple psychological mechanisms—conditioning responses through reinforcement patterns (Skinner, 1953), restructuring information processing and schema development (Bettman, 1979), and shaping behavior through observational learning and social proof (Bandura, 1977). Together, these behavioral, cognitive, and social mechanisms explain how AI reshapes each stage of consumer decision-making.

The Stimulus-Organism-Response Framework as Integrative Architecture

The Stimulus-Organism-Response (S-O-R) framework, originally developed by Woodworth (1929) and adapted for consumer behavior by Mehrabian and Russell (1974), provides an overarching architecture for understanding AI's multifaceted influence on consumer decision-making. This framework posits that environmental stimuli (S) affect individuals' internal states (O), which subsequently shape behavioral responses (R). Recent applications of S-O-R to AI-mediated consumer environments demonstrate its utility for capturing the complexity of human-technology interactions (Alghaswyneh, 2025).

In AI-mediated consumer contexts, stimuli encompass AI-generated recommendations, personalized content, conversational interfaces, and algorithmic curation. The organism component represents consumers' internal processing mechanisms including cognitive evaluations (perceived usefulness, trust, transparency), affective states (emotional responses, comfort with AI), and individual differences (technological readiness, expertise, demographic characteristics). These responses show up as what people do (what they buy, how they search, how much they use a platform), how they feel (loyalty and satisfaction), and how they learn and adapt (gaining skills or becoming dependent on the system) (Mani et al., 2025). S-O-R highlights that the same AI features can lead to different reactions because people differ internally, which matters given how varied consumers are in accepting AI (Jain et al., 2024).

Behavioral Learning Theory: AI as Conditioning Mechanism

Classical Conditioning and AI-Triggered Need Recognition

Behavioral learning theory says we learn behaviors by forming links between what happens around us and how we respond, as shown in Pavlov and Watson's work. Classical conditioning happens when a neutral cue is repeatedly paired with something meaningful until it triggers the same response on its own. AI recommendation systems act like advanced conditioning tools by linking situational cues (like time, place, or browsing history) with specific product suggestions (Kumar et al., 2024).

At the problem recognition stage, AI algorithms analyze behavioral patterns to identify temporal and contextual regularities that predict consumer needs. Through repeated exposure to algorithmically timed product recommendations consumers develop conditioned associations between environmental cues and consumption behaviors. These AI-created stimulus-response patterns can transform underlying needs into active desires through automated presentation at psychologically optimal moments, effectively conditioning need recognition itself (Tiwari & Namdeo, 2025).

This conditioning process extends beyond simple temporal associations. AI systems leverage multidimensional behavioral data to create complex conditional triggers incorporating location, weather, social context, and emotional state indicators. The sophistication of these conditioning mechanisms distinguishes AI from traditional marketing by enabling highly granular stimulus-response pairings that traditional mass marketing cannot achieve (Iqbal et al., 2025). However, this raises important questions about the boundary between facilitating genuine needs and artificially manufacturing desires through systematic conditioning.

Operant Conditioning and Reinforcement Learning in AI Systems

Operant conditioning, developed by Skinner, explains that behavior is shaped by its consequences: rewards increase the chance a behavior is repeated, while negative outcomes reduce it. In digital markets, AI systems apply this logic through reinforcement learning, constantly updating which recommendations to show based on how consumers respond (for example, clicks, purchases, or time spent). Over time, consumers learn that certain actions lead to benefits like relevant offers, discounts, or more personalized experiences, while the system simultaneously learns which prompts most effectively encourage those actions (Chen et al., 2023).

After purchase, AI-driven loyalty programs and engagement tools use ongoing rewards—points, status tiers, personalized perks, and targeted offers—to positively reinforce repeat buying and continued platform use. These rewards can follow different schedules, such as benefits every time a consumer buys or occasional, less predictable bonuses, both of which are known to strengthen habits like repurchase and brand loyalty. Research on reinforcement learning–based recommender systems shows that AI can fine-tune the timing and value of such incentives to maximize long-term customer engagement and lifetime value. (Afsar et al., 2022).

AI systems can also apply operant principles through negative consequences. When users disengage—such as abandoning carts or giving negative feedback—the system may reduce the attractiveness or frequency of personalized offers, slow responses, or limit access to certain benefits, which can act as negative reinforcement for those behaviors. This highly individualized use of reinforcement and punishment goes far beyond what traditional, one-size-fits-all marketing could do, marking a qualitative shift in how firms can shape consumer behavior through algorithmic control (Skinner, 1938).

Cognitive Learning Theory: AI and Information Processing Architecture

Schema Theory and AI-Mediated Knowledge Structures

Cognitive learning theory focuses on how people take in information, organize it, and use it to solve problems. Schema theory builds on this by explaining that people store knowledge in mental frameworks (schemas) that shape how they perceive, interpret, and remember information (Pappas, 2025). AI systems change how these schemas develop and are used in consumer decisions by controlling what information people see, in what order, and with what emphasis.

When consumers search for information, AI recommendation engines and chatbots filter and organize what is shown. Instead of exploring a wide range of options on their own, consumers are guided toward content that matches their predicted preferences and past behavior. This can make decision-making faster and easier, but it may also narrow what they learn, because they mostly see algorithmically selected options rather than a broader set of self-chosen alternatives (Gibson et al., 2023).

Studies on cognitive load and AI show that smart systems can present information in ways that help people build schemas more efficiently by managing the mental effort required for processing (Sweller, 2020). AI can cut out unnecessary details, tailor difficulty to the user's knowledge level, and structure content to support deeper understanding. At the same time, if consumers rely too heavily on AI to filter and interpret information, they may practice less independent thinking and evaluation, which can slow the development of their own information-processing and critical-thinking skills.

Heuristics and AI-Influenced Decision Rules

Cognitive learning theory recognizes that individuals develop heuristics—mental shortcuts that simplify complex decisions. In AI-mediated environments, consumers increasingly adopt AI-generated scores, rankings, and recommendations as decision heuristics, essentially delegating cognitive processing to algorithmic systems. This phenomenon, termed automation bias, reflects the tendency to over-rely on automated decision aids without critical assessment (Goddard et al., 2012).

At the evaluation stage, AI recommendation systems provide synthesized product comparisons, aggregated reviews, and predictive ratings that consumers integrate into simplified decision rules: 'choose the highest AI-rated option,' 'trust the algorithm's top recommendation,' or 'select items similar to AI suggestions.' These AI-influenced heuristics differ qualitatively from traditional heuristics (price-quality association, brand recognition) by incorporating dynamic, personalized assessments that adapt to individual consumer profiles.

The development of AI-reliant heuristics raises concerns about decision quality and consumer agency. While AI heuristics may improve efficiency and reduce cognitive effort, they potentially diminish consumers' analytical processing capabilities and critical evaluation skills. Furthermore, when AI recommendations embed commercial biases or algorithmic errors, uncritical heuristic adoption may produce systematically suboptimal decisions (Kahneman, 2011). Understanding these cognitive trade-offs requires examining both immediate decision outcomes and long-term effects on consumer learning and skill development.

Social Learning Theory: AI as Observational Model and Social Mediator

Observational Learning Through AI-Curated Social Proof

Social learning theory, developed by Bandura, explains that people learn by watching what others do and what happens to them. This kind of learning involves paying attention to others' behavior, remembering it, being able to copy it, and feeling motivated to do so. AI recommender systems tap into these processes by showing users what others have viewed, rated, or bought, turning peer behavior into a model to follow.

These systems aggregate many users' actions and present them as social cues, such as "customers who bought this also bought…" or "5,000 people are viewing this item." Such cues draw attention to certain products, make the behaviors easy to remember, make copying them as simple as one click, and add social pressure or validation that encourages people to follow along (Che & Hörner, 2018).

However, this AI-driven social learning is not the same as watching real people around you. Instead of observing friends or nearby others directly, consumers see curated, aggregated patterns that may only partially reflect real behavior. Because the platform decides which social information to show, this raises concerns about how authentic these signals are and whether they are being used more to steer choices than to inform them.

AI as Social Influence Agent and Artificial Social Entity

Contemporary AI tools are starting to act less like neutral information channels and more like social partners. When designers give conversational agents human-like names, personalities, and ways of speaking, people begin to respond to their suggestions as if they came from another person rather than a machine (Jain et al., 2024). This makes consumers more likely to interpret AI recommendations through the same social lenses they use for friends' or peers' advice.

These human-like qualities create new patterns of social learning. Instead of only copying or trusting human peers, consumers may start to model their behavior on what AI agents suggest, learning to trust the system's judgment and defer to its guidance. Over time, this raises important questions about how such interactions affect people's critical thinking, their relationships with other humans, and the risk of becoming overly dependent on AI for everyday decisions.

Integrative Framework: Hybrid Human-AI Learning Systems

These three learning perspectives—behavioral, cognitive, and social—work together at the same time in AI-mediated consumer decisions. Their combination creates a hybrid human–AI learning system in which both sides learn, adapt together over time, and show patterns that cannot be fully explained by looking at either humans or AI in isolation.

In traditional markets, learning mostly flows one way: consumers learn about products and brands. In AI-mediated settings, learning is reciprocal. Consumers learn from AI by developing conditioned responses to algorithmic cues, building schemas from AI-curated information, and copying behaviors highlighted through AI-presented social proof, while AI simultaneously learns from their clicks, purchases, and engagement and refines its algorithms based on that feedback (Afsar et al., 2022). This creates feedback loops in which consumer learning shapes how the system behaves next, and those updated system behaviors then influence what and how consumers learn.

From this integrated view, several propositions follow: (1) AI links contextual cues to consumption through repeated pairing, conditioning consumer responses; (2) AI-guided information search produces product schemas that are highly personalized but potentially narrower; (3) when AI recommendations are reliably accurate, consumers form heuristics that rely on those outputs; (4) by selectively highlighting peer actions, AI-curated social proof shapes observational learning; (5) ongoing interaction between consumers and AI generates feedback loops that steer how algorithms evolve; and (6) heavy, long-term reliance on AI may weaken consumers' own information-processing and critical-thinking skills.

LITERATURE REVIEW: AI INFLUENCE ACROSS DECISION STAGES

Stage 1: Problem Recognition

Problem recognition occurs when consumers notice a gap between their current and desired states (Howard & Sheth, 1969). Traditionally, this was triggered by internal needs or external cues, but AI now adds a third path: needs surfaced algorithmically through predictive analytics and pattern recognition. AI-driven recommendation systems and personalized ad platforms scan browsing histories, purchase records, and contextual data (such as time and location) to propose products before consumers consciously form a desire (Kumar et al., 2024).

From a behavioral learning perspective, this reflects conditioning: repeated exposure to AI prompts links specific cues with emerging needs. A consumer who often browses fitness gear at night may begin receiving gym-apparel offers at that time, turning a vague interest into clear purchase intent. Survey work shows that a large share of shoppers now use AI tools in their purchase decisions, and many trust algorithmic suggestions as much as—or even more than—peer recommendations (Mackey, 2025). A systematic review by Lopez-Lopez and Bara Iniesta (2025) finds that conversational AI can proactively surface needs in dialogue, speeding the shift from latent to active problem recognition.

These mechanisms raise ethical issues. When AI pinpoints and exploits moments of vulnerability—like targeting stressed users with indulgence products, the line between helping people recognize real needs and manufacturing desire becomes blurry (Kietzmann et al., 2018; Kumar et al., 2021). Designers and marketers must distinguish systems that clarify existing needs from those that create demand through behavioral conditioning and should use clear disclosure and welfare-oriented design rather than purely conversion-driven optimization.

Stage 2: Information Search

After recognizing a problem, consumers search for information through internal recall and external sources. Cognitive learning theory highlights how they encode, organize, and retrieve information using schemas and heuristics (Alba & Hutchinson, 1987). AI tools deeply reshape this stage. Conversational agents, recommender systems, and voice assistants filter, rank, and summarize options based on user data and past behavior, lowering search costs but also narrowing what people see (Lopez-Lopez & Bara Iniesta, 2025).

Natural language interfaces can condense reviews and feedback into personalized summaries, helping consumers process information faster and with less mental effort. Experimental evidence shows that generative AI interfaces reduce perceived cognitive load and speed evaluation, but also shrink the breadth of information consumers access (Lopez-Lopez & Bara Iniesta, 2025). As a result, schema development may become more efficient yet narrower: instead of building rich, multi-sided category knowledge, AI-reliant consumers form highly personalized but shallow schemas anchored in algorithmically selected content (Gibson et al., 2023).

This connects to filter bubbles, where algorithmic curation increasingly restricts exposure to content that fits prior preferences or engagement patterns (Kumar et al., 2021). When AI optimizes for clicks or time-on-site rather than informational quality, shoppers may miss critical comparisons, negative reviews, or alternative brands. Research on automation bias suggests that heavy reliance on AI-curated search results can reduce the likelihood of seeking disconfirming information and foster overconfidence in decisions made on incomplete evidence (Goddard et al., 2012). Effective trust in AI at this stage must therefore be calibrated: high enough to benefit from efficiency, but not so high that consumers stop checking or questioning algorithmic outputs

Stage 3: Evaluation of Alternatives

In evaluating alternatives, consumers compare options on relevant attributes and apply decision rules. Classic models emphasize multi-attribute evaluation with weighted criteria (Fishbein & Ajzen, 1975), while cognitive learning theory explains how heuristics simplify these comparisons. AI systems now take over much of this work by generating automated comparisons, predictive rankings, and personalized scores. They combine attribute data and user reviews to highlight key differences, reduce cognitive load, and speed choice (Lopez-Lopez & Bara Iniesta, 2025). Dynamic pricing engines also personalize perceived value by adjusting prices based on individual history and context.

However, these benefits come with risks. Consumers often treat AI rankings and scores as decision shortcuts without understanding how they were produced, which can embed commercial priorities or biased training data into the evaluation process (Goddard et al., 2012). Dual-process theory suggests that such AI support nudges people toward fast, intuitive (System 1) processing and away from slower, more analytical (System 2) thinking, especially in complex or high-stakes choices (Kahneman, 2011).

Explainability is therefore crucial. When recommenders offer clear reasons and criteria for their suggestions, consumers are more likely to engage deliberatively, adjust their own weights, and maintain agency. Proposition 3 in your framework—that the strength of AI-based heuristics depends on transparency—is consistent with this: explainable AI supports more appropriate heuristic use than opaque systems. At the same time, choice architecture effects (ordering, framing, default options) in AI interfaces leverage biases like anchoring and primacy, so consumers need metacognitive awareness of how interface design can steer their selections.

Stage 4: Purchase Decision

The purchase decision is where evaluation turns into action and includes choices about timing, channel, and payment. Self-determination theory holds that feeling autonomous is central to confidence and satisfaction with one's decisions (Deci & Ryan, 2000). AI influences this stage through dynamic pricing, personalized discounts, contextual nudges, and frictionless checkout flows. Studies show that trust in AI, perceived autonomy, and fit between recommendations and consumer goals all shape purchase likelihood (Jain et al., 2024; Kumar et al., 2021).

Anthropomorphic AI agents—those with human-like names, avatars, and conversational styles—can further increase trust and engagement, though effects vary by consumer segment and product type. People with high tech readiness and positive prior AI experiences tend to be more comfortable allowing AI to guide purchases, whereas those with strong privacy concerns or low literacy around AI may resist or disengage.

The core tension at this stage is between efficiency and autonomy. As AI pre-fills preferences, predicts quantities, and streamlines checkout, it reduces friction but can also make consumers feel that choices are being made *for* them rather than *by* them. Self-determination theory predicts that perceived loss of autonomy can trigger reactance and lower satisfaction, even when outcomes are objectively convenient (Deci & Ryan, 2000). Dark patterns—design choices that exploit scarcity, urgency, and social proof at scale—intensify this concern. Research on online dark patterns shows that tactics like "only 2 left," countdown timers, and exaggerated social proof can pressure decisions, harm long-term trust, and damage brand relationships, even if they lift short-term conversions (Kietzmann et al., 2018; Mathur et al., 2019). Cultural differences in tolerance for such tactics and expectations about AI involvement add further complexity for global marketers.

Stage 5: Post-Purchase Behavior

Post-purchase behavior includes satisfaction judgments, product use, complaints, repeat purchases, and loyalty. From a behavioral learning lens, positive reinforcement after purchase (e.g., rewards, recognition, smooth support) increases the likelihood of buying again (Skinner, 1953). AI enhances this stage through chatbots, predictive customer service, and personalized engagement programs that provide real-time assistance, anticipate issues, and deliver targeted follow-up recommendations. Evidence shows that AI-enabled service can improve satisfaction and loyalty when it is accurate, responsive, and tailored—often matching human agents for routine issues while lowering cost (Afsar et al., 2022).

Expectation-confirmation theory holds that satisfaction depends on the fit between pre-purchase expectations and actual experiences (Oliver, 1980). Highly personalized pre-purchase AI interactions may elevate expectations to levels that are hard to meet, raising the risk of disconfirmation. At the same time, AI-driven follow-ups—usage tips, positive review prompts, and curated social proof—can shape post-purchase evaluations and reduce dissonance, sometimes softening negative reactions even when objective performance is only average.

Finally, post-purchase engagement is also a phase of intensive data capture. Every interaction, search, complaint, and repurchase feeds back into AI models that further refine targeting and personalization. This can generate real value through better recommendations and service but also heightens privacy and surveillance concerns (Kumar et al., 2021). Research on long-term AI–consumer relationships emphasizes that clear communication about data practices and meaningful control over how data are used are essential to maintaining trust and sustaining loyalty in AI-mediated environments.

SYNTHESIS AND THEORETICAL INTEGRATION

Emerging Themes Across Decision Stages

Across the five decision stages, four cross-cutting themes stand out: trust, personalization–privacy trade-offs, autonomy, and individual differences. First, trust in AI is a core mediator at every stage. Trust in an AI system's accuracy, transparency, and underlying intent shapes how much consumers rely on recommendations, accept curated content, and feel comfortable with AI involvement in their choices (Jain et al., 2024; Mogaji, 2024). Calibrated trust—neither blind acceptance nor automatic rejection—allows people to enjoy efficiency and convenience while still exercising critical judgment (Jain et al., 2024; Jain et al., 2025).

Second, the tension between personalization benefits and privacy costs persists throughout the journey. AI-driven personalization can increase relevance, reduce effort, and improve outcomes, but it depends on continuous collection and analysis of behavioral and personal data (Kietzmann et al., 2018). Studies using privacy calculus theory show that many consumers weigh convenience and relevance against perceived privacy risks when deciding whether to accept personalization, affecting AI adoption, depth of engagement, and relationship quality over time (Culnan & Bies, 2003; Vlerick study on the personalization–privacy paradox, 2025).

Third, autonomy and perceived control repeatedly mediate how AI influences attitudes and behavior. When AI tools are experienced as supportive—helping consumers feel more informed and capable—they tend to boost satisfaction, engagement, and continued use (Deci & Ryan, 2000; Mogaji, 2024). When they are seen as overly directive or manipulative, they can trigger psychological reactance, distrust, and disengagement, highlighting the need for designs that reinforce rather than replace the consumer's sense of agency (Jain et al., 2024).

Finally, individual differences reliably moderate AI effects. Factors such as technological readiness, AI literacy, past experience, and demographic characteristics influence how people interpret AI outputs, how much they trust them, and how they balance benefits against risks (Jang, 2024; Du et al., 2024; Salhab & Aboushi, 2025). This suggests that one-size-fits-all AI interfaces are inadequate and that adaptive systems that tune explanation depth, control options, and intervention intensity to user characteristics are more likely to support positive outcomes across diverse consumer segments (Dwivedi et al., 2019; Achmadi et al., 2025)

IMPLICATIONS FOR LEARNING THEORY

AI integration requires extending traditional learning theories to cover joint human–machine learning. Consumers now learn not only from the content AI provides but also how to trust, question, or override its recommendations, while AI systems simultaneously update their models based on consumer behavior. This creates a co-evolutionary learning process that older consumer behavior models do not fully capture.

This paper's idea of learning displacement—where heavy AI use weakens people's own information-processing skills—is a new and important concept. If ongoing reliance on AI erodes consumers' ability to evaluate information, compare options, and make independent judgments, the consequences go beyond single purchases to affect overall consumer competence and market literacy. To test this, longitudinal studies are needed that track how critical-thinking and decision skills change over time as AI use increases.

The bidirectional learning dynamic also reshapes how we think about consumer–brand relationships. Classic relationship marketing assumes relatively stable consumers who gradually form preferences and loyalties. In AI-mediated contexts, both consumers and AI systems keep adapting to each other based on past interactions, creating path-dependent patterns of behavior and recommendations that can become hard to change once they are established.

RESEARCH GAPS AND FUTURE DIRECTIONS

Current research reveals several important gaps in both theory and practice. Longitudinal evidence on how AI-shaped decision-making affects consumer learning, skills, and autonomy over time is still rare. Most studies use cross-sectional designs, which cannot capture dynamic processes such as conditioning, schema change, or heuristic formation. Long-term panel studies following consumers over months or years of AI use are needed to evaluate feedback loops and possible learning displacement.

Cross-cultural work on AI's influence is also limited. Because cultures differ in individualism–collectivism, uncertainty avoidance, technology norms, and privacy expectations, findings based largely on Western samples may not generalize. Studies conducted in East Asian, South Asian, African, and Latin American contexts would greatly improve both theoretical reach and practical relevance.

In addition, there is not enough empirical research that directly compares decision quality and satisfaction for AI-assisted versus traditional decision processes. Many studies focus on attitudes and intentions rather than objective decision quality or long-term satisfaction. Experiments that compare AI-assisted and unassisted choices, with follow-up measures of satisfaction and post-purchase behavior, would provide clearer evidence of AI's net impact on consumer welfare.

Research on vulnerable groups—such as older adults, people with cognitive or digital literacy limitations, and consumers in lower-income markets—is especially scarce. If AI mechanisms operate differently or more strongly for these segments, tailored protections and adaptive design will be necessary. Useful questions include: (1) How do AI conditioning effects differ between high- and low-literacy users? (2) Which transparency formats best support calibrated trust across demographic groups? (3) How do cultural values shape the autonomy–efficiency trade-off? (4) Which interface features maintain consumer agency while still delivering AI efficiency? (5) How does AI reliance influence long-term information-processing skills under different usage patterns?

Methodologically, tightly controlled experiments that isolate specific AI features and their psychological effects would sharpen theory. Deeper collaboration across computer science, psychology, philosophy, and ethics can also clarify AI's multifaceted impact on consumer choice. Finally, computational models that simulate consumer–AI learning over time can complement empirical work by generating concrete, testable predictions about emergent patterns in hybrid human–AI learning systems.

IMPLICATIONS

Managerial Implications

Marketing implications across the five stages can be summarized around trust, autonomy, and long-term value, rather than short-term conversion. Marketing practitioners need to recognize that AI's performance depends heavily on consumer trust and a sense of control. Firms should be open about when and how AI is used, offer clear explanations for recommendations, and preserve meaningful user choices. Personalization efforts must be balanced against privacy risks and the likelihood that consumers will push back if they feel manipulated.

At problem recognition, AI should help surface real, pre-existing needs instead of creating artificial ones. Timely, relevant prompts that reflect genuine behavior patterns can strengthen trust and long-term engagement, whereas aggressive conditioning that stirs up unnecessary wants invites regulatory risk and consumer backlash. During information search, AI curation should widen—not narrow—the field of view by actively including comparisons, alternative brands, and critical reviews, which supports better decisions and positions AI as a credible information partner.

In evaluation and purchase, explainable AI that shows *why* an option is recommended helps consumers think more carefully and feel better about their choices. Rather than tuning algorithms only for immediate sales, designers should optimize for long-term consumer outcomes—such as satisfaction and confidence—because these ultimately drive higher lifetime value. After purchase, AI should prioritize real value creation through usage tips, problem solving, and learning support, instead of focusing mainly on nudging repeat purchases. Ethical use here requires honesty about ongoing data collection, clear consent options, and a transparent value exchange so consumers understand what they gain in return for their data.

CONCLUSION

AI now deeply shapes every step of how consumers decide what to buy, using personalization, automation, and continual learning to reshape traditional processes. By tracing AI's role across the five decision stages and linking it to behavioral, cognitive, and social learning theories, this review clarifies how AI reshapes what and how consumers think, feel, and do throughout the journey.

The integrated framework proposed here extends existing theory in several ways. It recasts consumer learning as a joint human–AI process, governed by bidirectional feedback and co-evolution between people and algorithms, offering tools to study emerging patterns that single theories cannot fully explain. It also introduces learning displacement—the idea that heavy reliance on AI may weaken independent cognitive skills—as a new construct with serious implications for long-term consumer welfare and market literacy.

Although AI delivers major efficiency gains at each stage, it also raises ongoing concerns about autonomy, privacy, decision quality, and ethics. A recurring theme is the trade-off between efficiency and autonomy, which implies that AI in consumer contexts must be designed with psychological wellbeing in mind, not just technical performance. Responsible deployment demands transparency, real consumer control, and systems that support rather than erode human agency.

As AI capabilities grow, balancing technological efficiency with human agency will remain a core challenge for scholars, managers, and regulators. Hybrid human–AI decision systems mark a structural shift in consumer behavior that calls for broader theory, new methods, and a renewed insistence that technology ultimately serve human flourishing. Future research should emphasize long-term (longitudinal) evidence, cross-cultural diversity, and the experiences of vulnerable groups to ensure that the gains from AI-mediated commerce are widely and fairly shared.

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