Wahpiyudin et al. *Journal of Consumer Sciences* (2025), *10*(1), 27-58
DOI: https://doi.org/10.29244/jcs.10.1.27-58

JOURNAL OF CONSUMER SCIENCES

CONSUMER BEHAVIOR | RESEARCH ARTICLE

Determining AI-Based Learning Adoption Model for Students in Entrepreneurship Education: A Design Thinking Approach

Cep Abdul Baasith Wahpiyudin[1*)], Sabda Alam Muhammadan[1], Riska Amalia[1], Adelia Chrisanta[1], Asep Taryana[1]

Article history:
Received
November 3, 2024

Revision submit
December 5, 2025
December 15, 2025

Accepted
December 31, 2024

Available online
January 31, 2025

Author Affiliation:
[1]School of Business, IPB University, SB-IPB Building, Jl. Raya Pajajaran, Bogor, West Java 16151, Indonesia

*Corresponding author:
cepbaasith@gmail.com

Background: Student interest in entrepreneurial pursuits remains low, despite the significant contributions of entrepreneurship to economic growth.
Purpose: This study investigates the factors influencing IPB students' interest in adopting AI-based entrepreneurship learning through the lens of design thinking, emphasizing the role of communication methods and their impact on motivation and attitudes.
Methods: This study adopts a mixed-method design, combining quantitative and qualitative approaches. Quantitative data were collected via an online survey from 173 IPB students, with 166 valid responses after data cleaning. Quantitative analysis was conducted using descriptive statistics (SPSS 25) and Partial Least Squares Structural Equation Modeling (PLS-SEM). The qualitative aspect involved a SCAMPER analysis within the design thinking framework to explore AI integration in entrepreneurship education. The PICOS framework was applied to explore the factors influencing AI adoption in higher education comprehensively. This mixed-method approach provides a holistic understanding of AI adoption in educational contexts.
Findings: Results indicate that learning motivation significantly affects students' intentions to engage with AI-based systems, positively impacting attitudes toward AI. Perceived ease of use also positively influences learning motivation and perceived usefulness, although perceived usefulness does not directly impact learning motivation. Additionally, interpersonal interactions and mass media positively influence attitudes and perceived usefulness, while awareness does not have a significant effect.
Conclusion: Expanding AI adoption in entrepreneurship education requires strategic communication, mainly focusing on Design Thinking's empathize phase to understand student challenges. By iteratively proposing AI tools through the prototype phase, institutions can develop user-friendly, engaging solutions tailored to student needs, fostering higher adoption and engagement in entrepreneurship learning.
Research implication: These insights suggest that targeted communication strategies, including design thinking principles, can support broader AI adoption, enhance students' entrepreneurial learning experiences, and foster a new generation of tech-savvy entrepreneurs.

Keywords: AI-based system, design thinking, entrepreneurship, planned behavior, technology acceptance
JEL Classification: D12, L26, M31

Cep Abdul Baasith Wahpiyudin

ABOUT THE AUTHORS

Cep Baasith Abdul Baasith Wahpiyudin's primary research interest is consumer protection, to which he has contributed actively by working with consumer protection organizations. He is currently pursuing his master's degree in the Department of Management and Business at IPB University under a prestigious, fully funded LPDP scholarship. He can be reached at cepbaasith0@gmail.com.

Sabda Alam Muhammadan is a Civil Servant at the Ministry of Finance (Indonesia). He holds a Diploma in Accountancy from the State College of Accountancy (Indonesia) and a Bachelor's degree in Management from Open University (Indonesia). He can be reached via sabdaalamm.sam@gmail.com

Riska Amalia is a Bachelor of Communication majoring in Public Relations at Pakuan University Bogor, with a final research focus on communication strategies on Instagram's social media. She can be reached at riskaalmalia58@gmail.com

Adelia Chrisanta has completed her bachelor's degree at Hasanuddin University in Agrotechnology Study Program, Department of Plant Pest and Disease. Her research focuses on plant pests. She can be reached through email at chrisantadelia@gmail.com

Asep Taryana is a serves as a lecturer in the Department of Management and Business at the School of Business, IPB University, where he is dedicated to educating and mentoring future leaders in business and entrepreneurship. Dr. Sujana's expertise focuses on strategic management and the development of entrepreneurial skills, making him a valuable resource for students and colleagues alike. For inquiries or potential collaborations, Asep Taryana can be reached via email at kang.astar@apps.ipb.ac.id.

PUBLIC INTEREST STATEMENT

This research addresses the challenges associated with adopting AI-based learning in entrepreneurship education, specifically among students at IPB University. Despite AI's potential to enhance entrepreneurial skills, adoption rates are hindered by issues such as a limited understanding of AI functionalities, perceived complexity, and the need for more accessible training resources.

Additionally, a lack of awareness regarding AI's practical applications in business impacts students' motivation to engage with these tools. By examining these barriers and identifying effective communication channels, this study provides insights for educational institutions on supporting AI integration, ultimately fostering a more tech-savvy generation of entrepreneurs.

JOURNAL OF CONSUMER SCIENCES

1. Introduction

Entrepreneurship has long been recognized as a critical driver of economic growth and technological innovation, catalyzing efficiency, productivity, and competitiveness across industries (Sagar et al., 2023). It serves as a pivotal mechanism for sustainable development, fostering job creation, economic diversification, and the integration of advanced technologies into business operations. According to Crudu (2019), entrepreneurial activity, particularly the Total Early-stage Entrepreneurial Activity (TEA) innovation rate, is positively associated with higher economic development and income levels. In developed nations, entrepreneurship is typically driven by opportunities for enhancement and innovation rather than necessity, establishing it as a fundamental contributor to resilience and economic growth. However, merely increasing entrepreneurial endeavors does not automatically lead to economic growth; the quality and innovative potential of these ventures drive meaningful contributions (Crudu, 2019).

University students hold a strategic role as emerging leaders with significant potential in the entrepreneurial landscape. As the future workforce, they possess the capacity to create jobs and leverage cutting-edge technologies for entrepreneurial growth and transformation. Research highlights their critical role in founding start-ups and strengthening entrepreneurial ecosystems. For instance, Galvão et al. (2020) underscore students' ability to foster a culture of innovation, impacting communities and industries. Nabi et al. (2017) argued that students are well-positioned to drive sustainable economic change with their blend of knowledge, innovation, and resources. This reinforces the importance of entrepreneurship education in equipping students with competencies for a rapidly evolving global economy. Apostu et al. (2024), Blanco-González et al. (2024), Bardales-Cárdenas et al. (2024), and Syed et al. (2024) further assert that improving entrepreneurship education is crucial to bridging the gap between students' potential and their actual contributions to economic development.

Despite this potential, a significant gap exists between students' entrepreneurial potential and engagement. Studies reveal that students' interest in entrepreneurship remains low despite efforts to improve teaching methods (Sari & Hairunisya, 2022). Entrepreneurship in Indonesia is relatively low compared to other countries, with high unemployment among educated individuals (Lestari, 2023). Students from accounting and management programs are only categorized as "Quite Potential" in terms of entrepreneurial character (Prasetiawan et al., 2021). Other studies emphasize the importance of social support and achievement drive in fostering entrepreneurial interest (Primandaru, 2017). While self-efficacy and technopreneurship literacy positively influence entrepreneurial interest, barriers such as limited skills (Saputra et al., 2021) and restricted financial access (Rusu et al., 2022) hinder students from pursuing entrepreneurship. Addressing these barriers requires a comprehensive approach to mitigate both practical and psychological challenges, empowering students to engage in entrepreneurial activities.

Artificial intelligence (AI) has emerged as a transformative tool to reshape the entrepreneurial landscape by reducing traditional barriers to entry. Vocke et al. (2019) found that AI technologies enhance operational efficiency and provide sophisticated tools for market analysis, inventory management, and customer relationship management. Ahmed and Ganapathy (2021) argue that AI simplifies access to critical information and training, enabling aspiring entrepreneurs to develop business skills effectively. AI applications in financial technology extend funding opportunities through micro-loans and AI-powered credit assessments, democratizing access to business capital (Kshetri, 2021). Additionally, AI-driven education introduces opportunities for personalized learning, aligning educational experiences with students' needs.

JOURNAL OF CONSUMER SCIENCES

Despite extensive research on AI adoption, gaps remain in understanding how communication channels influence students' interest in using AI for entrepreneurial learning (Chai et al., 2020; Chou et al., 2022; Sayaf et al., 2022; Labrague et al., 2023; Li, 2023). By integrating TAM, TPB, and Communication Channel Model, alongside design thinking and SEM, the research provides a framework for AI adoption, equipping students with tools to thrive as innovative entrepreneurs in a technology-driven economy.

2. Literature Review

2.1 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior is a key framework for understanding individual intentions and behaviors, emphasizing three core factors: attitude toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). These components directly influence behavioral intentions, which, in turn, predict actual behavior (Ajzen, 1985). Attitude reflects an individual's evaluation of behavior, where positive attitudes generally lead to a stronger intent to perform the behavior, especially when new technology is involved. Subjective norms capture perceived social pressures, with research by Simamora and Djamaludin (2020) highlighting their significant impact on technology adoption. Perceived behavioral control refers to the ease or difficulty in performing the behavior, shaped by resources, knowledge, and experience (Hagger et al., 2022). Internal psychological factors, such as motivation and locus of control, also influence behavioral intentions. Putri and Simanjuntak (2020) found that individuals with strong motivation and a sense of control over their actions are more proactive in decision-making, reinforcing the role of psychological readiness. In this study, TPB serves as the theoretical foundation for exploring IPB University students' intentions to adopt AI-based learning tools in entrepreneurship. By examining students' attitudes, subjective norms, and perceived behavioral control, TPB offers valuable insights into the factors motivating students to embrace AI in education.

2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is essential for understanding technology adoption in organizational, professional, and educational contexts. TAM emphasizes two key constructs: perceived usefulness and perceived ease of use, both critical in shaping users' intentions to engage with new technologies. Perceived usefulness refers to the belief that technology enhances performance or helps achieve goals, with its relevance being especially important in education (Davis et al., 1989). In this study, it reflects students' perceptions of AI tools' ability to improve entrepreneurship education. Perceived ease of use, in turn, refers to how intuitive and user-friendly technology is. According to TAM, technologies perceived as easy to use face fewer barriers to adoption (Davis, 1989). In this context, it pertains to how students perceive the accessibility of AI tools in their learning environment. Thus, TAM provides a framework for understanding how perceptions of technology's usefulness and ease of use influence students' motivations and intentions, particularly in adopting AI tools in entrepreneurship education.

2.3 Design Thinking and Its Influence on AI-Based Learning Formulation Strategies

Design Thinking has emerged as a leading user-centered framework for addressing complex problems in various fields, particularly in educational contexts where adaptability and personalization are critical (Mirra & Pugnale, 2022). Characterized by empathy, ideation, and iterative prototyping, design thinking strongly emphasizes understanding and addressing user needs. This approach is highly relevant to AI integration in education, as it aligns well with AI technologies' adaptability and customization potential. Studies by Cautela et al. (2019) and Tang et al. (2022) demonstrate that incorporating Design Thinking into AI-based educational strategies enhances engagement and interaction, ultimately leading to more effective learning outcomes.

In the context of this study, design thinking is applied to ensure that AI-based learning tools for entrepreneurship education are functional, intuitive, engaging, and responsive to students' needs. The iterative design thinking process of understanding students' preferences, generating ideas, and prototyping solutions is essential in fostering an AI learning environment aligned with students' expectations, thereby promoting greater satisfaction, engagement, and motivation to use AI for educational purposes.

2.4 Communication Channels

Communication channels, such as interpersonal communication, mass media, and awareness campaigns, are vital in promoting technology adoption by disseminating information, building trust, and reinforcing positive attitudes (Tran & Corner, 2016; Madjdian et al., 2024). Interpersonal communication, including peer discussions, mentor-mentee relationships, and collaborative interactions, fosters familiarity and relatability, shaping attitudes toward new technologies. Public health and educational campaigns have successfully used interpersonal communication to enhance understanding and encourage adoption (Shah & Wei, 2022; Karletsos et al., 2021). Meanwhile, mass media increases public awareness and familiarity with technologies, providing a broad foundation that can later be contextualized through interpersonal interactions, as seen in mobile banking or food safety campaigns (Cummings & Ingber, 2024; Horowitz et al., 2024).

Awareness campaigns integrate interpersonal and mass communication to communicate a technology's benefits effectively. Integrated efforts, such as breast cancer awareness and domestic violence prevention, have proven successful by combining broad media outreach with personalized, targeted impact (Cardoso et al., 2023; Dzidzornu et al., 2024). In digital marketing, structured communication strategies enhance brand engagement and loyalty (Bowden & Mirzaei, 2021). This study investigates how these communication channels influence students' attitudes and perceptions of AI-based learning tools in entrepreneurship education. By analyzing their individual and collective impact, the research provides valuable insights for designing effective communication strategies that promote adopting and sustained use of educational technologies to foster skill development and career readiness (Bowden & Mirzaei, 2021; Shah & Wei, 2022).

2.5 Previous Research Supporting Hypotheses

2.5.1 Effect of learning motivation on behavioral intention towards AI-Based systems

Learning motivation significantly influences the adoption of AI-based systems in education. According to TPB, the drive to achieve academic goals and social pressures from peers and educators shape students' intention to use technology (Ajzen, 1985; Ajzen, 1991). Motivated learners value AI tools for skill enhancement and academic success (AlGerafi et al., 2023). This aligns with TAM, which highlights that intrinsically motivated individuals perceive technology as essential for learning (Davis, 1989; Hubert et al., 2019).

JOURNAL OF CONSUMER SCIENCES

In entrepreneurial education, students actively utilize AI to develop competencies and remain competitive (Apostu et al., 2024; Blanco-González et al., 2024; Bardales-Cárdenas et al., 2024; Syed et al., 2024). Learning motivation fosters engagement with AI systems, reinforcing their role as vital tools for academic and professional growth (Winkler et al., 2023). Based on these findings, the hypothesis is proposed as follows:

H1: Learning motivation has a significant positive effect on behavioral intention towards AI-based systems.

2.5.2 The Effect of Attitude toward AI-Based Systems on Learning Motivation

Attitudes toward technology play a crucial role in shaping students' motivation, particularly in educational settings, where the perceived relevance and utility of tools like AI significantly influence engagement. In line with the Technology Acceptance Model (TAM), positive attitudes serve as a primary driver of both motivation and behavioral intentions, with students who view AI favorably being more likely to integrate it into their academic practices (Davis, 1989). Studies by AlGerafi et al. (2023) support this view, showing that students with favorable attitudes toward AI-based systems exhibit higher motivation and engagement, viewing AI as a valuable tool for academic achievement and skill enhancement. This perception drives students to explore and adopt AI, aligning the technology with their academic and personal goals (Li, 2023).

Favorable attitudes toward AI also create a learning environment where students feel confident navigating the technology, fostering intrinsic motivation. Roy et al. (2022) found that students who view AI positively are more motivated to interact with AI tools, seeing them as integral to success. This positive disposition encourages curiosity and reinforces motivation, as students perceive AI as essential to their academic progress. As students gain confidence in using AI and explore its advanced features (Ahmed & Ganapathy, 2021), their engagement deepens, reinforcing TAM's assertion that positive attitudes lead to sustained use and satisfaction. Overall, a constructive attitude toward AI fosters lasting motivation, encouraging students to fully embrace AI systems as essential components of their educational journey. Based on these insights, the following hypothesis is proposed:

H2: Attitude toward AI-based systems has a significant positive effect on learning motivation.

2.5.3 The Effect of Perceived Usefulness on Learning Motivation

Perceived usefulness, a key component of the Technology Acceptance Model (TAM), significantly influences technology adoption by shaping students' motivation to integrate tools that enhance performance and academic success (Davis, 1989). In educational contexts, students are more likely to adopt AI-based systems when they perceive these tools as valuable for improving efficiency and supporting skill acquisition. Research by Mohr and Kühl (2021) supports this, showing that students motivated by AI's perceived academic and career benefits are more inclined to engage with these tools, integrating them into their routines to streamline workloads and enhance entrepreneurial skills. This aligns with TAM's premise that perceived usefulness drives motivation and engagement (Davis et al., 1989; Rokhim et al., 2022).

Perceived usefulness also fosters sustained technology use by enhancing students' motivation and attitudes toward continuous engagement. Studies by AlGerafi et al. (2023) reveal that students motivated by AI's usefulness, such as personalized feedback and interactive learning, are more likely to explore and continuously use these tools.

This is especially crucial in entrepreneurial education, where AI tools offering business simulations and data-driven insights align with students' goals, further driving deeper engagement (Deshpande et al., 2024). By demonstrating its value in achieving both immediate and long-term academic goals, perceived usefulness plays a central role in sustaining students' motivation and ensuring ongoing technology adoption (Ahmed & Ganapathy, 2021; Nedeljković & Petrović, 2023; Almulla, 2024). Based on these insights, the following hypothesis is proposed:

H3: Perceived Usefulness has a significant positive effect on Learning Motivation.

2.5.4 The Effect of Perceived Ease of Use on Learning Motivation

Perceived ease of use, as outlined by the Technology Acceptance Model (TAM), refers to the extent to which individuals believe a technology is effortless and user-friendly (Davis, 1989). In educational contexts, this concept is crucial as students prioritize tools that are accessible and intuitive. Technologies perceived as easy to navigate reduce cognitive load, allowing students to focus on learning rather than dealing with technical challenges. This simplicity fosters confidence, positively influencing motivation to adopt and engage with the technology (Elkaseh et al., 2016; Deshpande et al., 2024). Research by AlGerafi et al. (2023) supports this, showing that students who find AI tools intuitive and user-friendly exhibit higher engagement levels, aligning with TAM's assertion that straightforward technologies are more likely to be adopted and consistently used (Davis et al., 1989).

Additionally, reducing cognitive demand by providing user-friendly technologies supports theories that emphasize cognitive load as a motivational factor. Students using AI tools with minimal obstacles feel more competent and effective, enhancing intrinsic motivation (Gupta, 2020; Nedeljković & Petrović, 2023; Almulla, 2024). This positive dynamic encourages long-term use as accessible AI tools become integral to students' educational experiences. By streamlining the adoption process, perceived ease of use fosters sustained motivation, supporting students in their academic success and reinforcing the role of technology in achieving educational goals. Based on these insights, the following hypothesis is proposed:

H4: Perceived ease of use has a significant positive effect on learning motivation

2.5.5 The Effect of Communication Channels (Interpersonal Communication, Mass Media, Awareness) on Attitude toward AI-Based Systems

Communication channels, such as interpersonal communication, mass media, and awareness, play a crucial role in shaping students' attitudes toward adopting new technologies. Interpersonal communication, particularly with peers sharing similar academic or professional goals, helps students exchange relatable experiences, fostering a supportive environment that encourages favorable views toward AI. Research by Mannan et al. (2017) shows that interactions with experienced peers enhance positive attitudes by validating technology's utility, making adoption seem more approachable. This is supported by Deepa and Baral (2022), who highlight the importance of integrated communication in shaping internal attitudes and creating a coherent environment within educational institutions.

Mass media also significantly influences attitudes by broadening exposure to AI and its benefits. Tran and Corner (2016) argue that mass media amplifies awareness, especially with informative campaigns, fostering a continuous stream of positive portrayals that reinforce favorable perceptions of AI. Studies by Chou et al. (2022) and Sicilia and

Palazón (2023) emphasize that consistent mass media messaging enhances engagement and positive attitudes, ensuring reliable information about complex innovations like AI.

Awareness, cultivated through interpersonal communication and mass media, further strengthens students' attitudes by clearly understanding AI's potential. Increased awareness demystifies technology, reducing resistance and promoting a positive outlook. Lee and Chung (2023) highlight the importance of transparency and credibility in media communication, which applies to education by promoting trustworthy information about AI. Research by Uribe et al. (2022) also suggests that exposure to credible media and trusted influencers boosts positive attitudes toward technology. Together, these communication channels foster familiarity and clarity, helping students view AI as a valuable academic tool rather than a complication, thus reinforcing positive attitudes toward its adoption. Based on previous studies, the following hypotheses are proposed:

H5: Interpersonal communication significantly positively affects attitudes toward AI-based systems.
H6: Mass media significantly positively affects attitudes toward AI-based systems.
H7: Awareness has a significant positive effect on attitudes toward AI-based systems.

2.5.6 The Effect of Communication Channels (Interpersonal Communication, Mass Media, Awareness) on Perceived Usefulness

Effective communication channels are essential in shaping students' perceptions of a technology's usefulness, especially in academic settings where the relevance and practical utility of a technology are key factors in adoption. Interpersonal communication plays a critical role by allowing students to discuss the advantages of AI-based systems with peers and mentors, fostering a deeper understanding of how these tools can enhance academic performance. Hubert et al. (2019) found that students who engaged in discussions about AI's applications were more likely to perceive it as useful, as these conversations provided firsthand insights into the technology's capabilities and its relevance to educational goals. Deepa and Baral (2022) further emphasize that effective communication integration creates an environment of trust and attraction, reinforcing positive perceptions of new technology. Mass media also significantly influences perceived usefulness by exposing students to various applications and benefits of AI. Shang et al. (2021) highlight that media campaigns that present concrete examples of AI's practical benefits enhance students' perceptions, particularly in contexts where efficiency and academic success are prioritized. Hsieh and Lee (2021) argue that the social and informational richness of media communications influences perceptions of AI's usefulness, further supporting adoption.

Through interpersonal communication and mass media, awareness amplifies perceived usefulness by helping students understand AI's potential benefits. With greater awareness, students are better positioned to recognize the value AI adds to their learning processes. Yen (2023) found that increased awareness of integrated platform capabilities leads to stronger perceptions of usefulness and sustained engagement. This understanding encourages students to view AI as a tool that facilitates goal achievement and improves academic performance, motivating them to adopt and engage with AI-based systems. Based on previous studies, the following hypotheses are proposed:

H8: Interpersonal communication has a significant positive effect on perceived usefulness.
H9: Mass media has a significant positive effect on perceived usefulness.
H10: Awareness has a significant positive effect on perceived usefulness.

JOURNAL OF
CONSUMER SCIENCES

2.5.7 The Effect of Communication Channels (Interpersonal Communication, Mass Media, Awareness) on Perceived Ease of Use

Communication channels also play a pivotal role in influencing students' perceptions of ease of use, particularly in shaping familiarity and reducing perceived complexity. Interpersonal communication with experienced users can make technology more accessible by providing hands-on insights and practical advice. For example, Mannan et al. (2017) found that students who discuss AI with knowledgeable peers better understand its functionalities, reducing apprehension and increasing perceived ease of use.

Mass media and awareness initiatives also demystify AI by breaking down its complexity, enabling students to view it as a more user-friendly option for academic purposes. Kumar and Singh (2022) explain that exposure to simplified demonstrations and relatable content in media can alleviate concerns about technological challenges. By fostering familiarity, media channels help students perceive AI as intuitive and accessible, thus encouraging adoption. Awareness campaigns that educate students on the straightforward aspects of AI can further increase perceived ease of use, making the technology more approachable and encouraging positive engagement (Gonzalez & de la Torre, 2020; Miller & Hwang 2022; Alharbi & Alzahrani, 2023; Baker & Inventado, 2023). Based on previous studies, the following hypotheses are proposed:

H11: Interpersonal communication significantly positively affects perceived ease of use.
H12: Mass media significantly positively affects perceived ease of use.
H13: Awareness has a significant positive effect on perceived ease of use.

2.5.8 The Effect of Perceived Ease of Use on Perceived Usefulness

The relationship between perceived ease of use and perceived usefulness is central to the Technology Acceptance Model (TAM), as technologies that are easy to use are often seen as more valuable. When students find AI intuitive, they are more likely to perceive it as a helpful tool for achieving their learning goals (Roy et al., 2022). Research on IoT systems and mobile commerce confirms that easy-to-use technologies reduce cognitive strain and increase perceived usefulness (Dong et al., 2017; Pipitwanichakarn & Wongtada, 2021). Similarly, studies in online teaching demonstrate that accessible technologies are perceived as more valuable by instructors (Barua & Urme, 2023).

This principle extends to various fields. Intuitive system design in hospitality reduces resistance to new technologies, enhancing their perceived value (Kim et al., 2023). Simple interfaces in mobile apps, mobile payments, and digital marketing also strengthen perceived usefulness, driving user engagement and loyalty (Stocchi et al., 2019; Kalinić et al., 2020; Mafe & Blas, 2010; Duffett & Maraule, 2023). Ease of use encourages initial adoption and sustains long-term engagement, aligning with TAM's assertion that ease of use facilitates a seamless user experience, which, in turn, enhances the perceived value of the technology (Davis, 1989). Based on previous studies, the following hypothesis is proposed:

H14: Perceived ease of use has a significant positive effect on perceived usefulness.

JOURNAL OF
CONSUMER SCIENCES

3. Conceptual Framework

The conceptual framework in Figure 1 combines three foundational theories: TPB, TAM, and the Communication Channels Model. It explains the factors influencing students' behavioral intention to adopt AI-based learning systems.

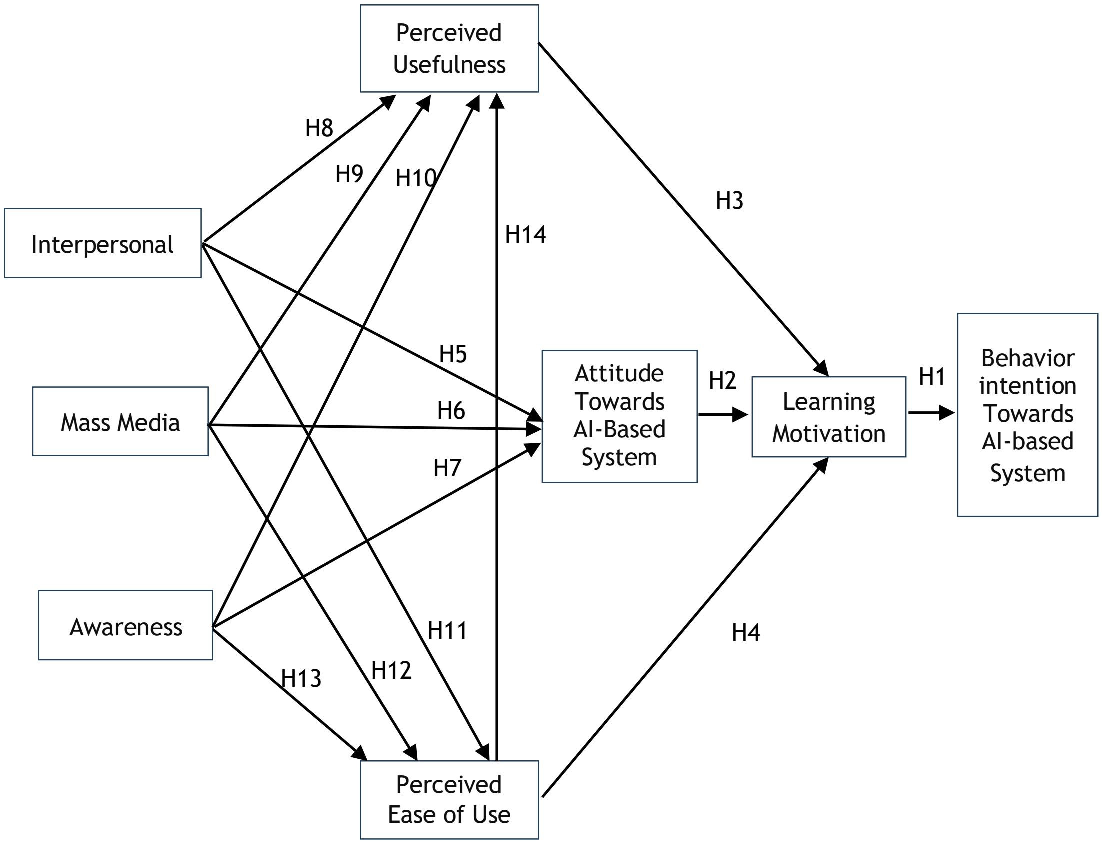

Figure 1. Conceptual framework of behavioral intention towards AI-based systems in learning, influenced by communication channels, perceived usefulness, perceived ease of use, attitudes, and learning motivation

The hypotheses of this study are as follows:

H1: Learning Motivation has a significant positive effect on behavioral intention toward AI-based systems.
H2: Attitude towards AI-based systems significantly positively affects learning motivation.
H3: Perceived usefulness has a significant positive effect on learning motivation.
H4: Perceived ease of use has a significant positive effect on learning motivation.
H5: Interpersonal communication significantly positively affects attitudes toward AI-based systems.
H6: Mass media significantly positively affects attitudes toward AI-based systems.
H7: Awareness has a significant positive effect on attitude toward AI-based systems.
H8: Interpersonal communication has a significant positive effect on perceived usefulness.
H9: Mass media has a significant positive effect on perceived usefulness.
H10: Awareness has a significant positive effect on perceived usefulness.
H11: Interpersonal communication significantly positively affects perceived ease of use.
H12: Mass media significantly positively affects perceived ease of use.
H13: Awareness has a significant positive effect on perceived ease of use.
H14: Perceived ease of use has a significant positive effect on perceived usefulness.

JOURNAL OF CONSUMER SCIENCES

4. Methods

4.1 Research Design

This study employs a mixed-methods design, combining quantitative and qualitative approaches to examine causal relationships among communication channels (interpersonal, mass media, awareness), perceived ease of use, perceived usefulness, attitude toward AI-based systems, learning motivation, and behavioral intention to adopt AI-based systems in education. Data collection primarily uses an online survey analyzed through Structural Equation Modeling (SEM) to measure variable relationships.

The research is grounded in the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Communication Channels Model, offering a robust framework for understanding technology adoption in higher education.

Additionally, the SCAMPER framework supports qualitative analysis, exploring how AI can enhance entrepreneurship education by fostering innovative teaching methods. This complements quantitative findings and provides richer insights into AI integration. The study also adopts the PICOS framework to holistically examine factors influencing AI adoption, ensuring a comprehensive understanding of the research problem.

4.2 Sampling

The target population consists of university students in West Java who are enrolled in entrepreneurship programs. A purposive sampling method was used to ensure that participants met the criteria relevant to the study's focus on entrepreneurial learning and AI adoption. This non-probability sampling technique allowed for selecting individuals with specific characteristics central to the research.

The inclusion criteria were: (1) Indonesian citizenship, (2) active enrollment at IPB University (undergraduate, graduate, and doctoral levels), (3) current or past participation in entrepreneurship or business-related learning, and (4) a clear interest in pursuing entrepreneurship as a career.

The sample size was determined based on the requirements for Structural Equation Modeling (SEM), which recommends a minimum of 100 respondents for reliable path analysis (Hair et al., 2017). Initially, 173 responses were gathered; after data cleaning to remove duplicates and incomplete responses, the final sample size was 166, resulting in a response rate of 95.9% ((166/173) x 100%).

4.3 Measurement

This study measured constructs using multi-item scales adapted from validated sources, with responses on a four-point Likert scale (1 = strongly disagree to 4 = strongly agree). Constructs included interpersonal communication, mass media, awareness, perceived ease of use, perceived usefulness, attitude toward AI-based systems, learning motivation, and behavioral intention. Table 1 summarizes each construct's definitions, indicators, and reliability metrics, including Cronbach's Alpha, rho_A, CR, and AVE.

JOURNAL OF
CONSUMER SCIENCES

Table 1. Operational definitions, indicators, and reliability of study variables

Variables & Operational Definition	Indicators	Sources	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Interpersonal (IC) Information and recommendations from close contacts about AI-based systems.	IC1: Information from close contacts (friends, family).	Mannan et al., 2017	1.000	1.000	1.000	1.000
Mass Media (MM) AI-based system information through mass media like TV, newspapers, or internet.	MM1: AI information via mass media.	Mannan et al., 2017	1.000	1.000	1.000	1.000
Awareness (AW) General awareness of AI-based systems facilitated by educational outreach.	AW1: Awareness fostered through institutional promotions.	Mannan et al., 2017	1.000	1.000	1.000	1.000
Perceived Ease of Use (PEOU) Perceived simplicity of using AI-based systems for learning purposes.	PEOU1 - PEOU5: Statements on ease of learning and using AI tools.	Li, 2023	0.936	0.937	0.951	0.796
Perceived Usefulness (PU) The belief that AI-based systems will enhance learning efficiency.	PU1 - PU5: Statements on the utility of AI for educational purposes.	Li, 2023	0.915	0.916	0.937	0.748
Attitude toward AI (Att) Positive or negative evaluation of AI-based systems for learning.	ATT1 - ATT4: General attitudes toward AI in education.	Li, 2023	0.858	0.866	0.903	0.698
Learning Motivation (LM) Motivation based on interest, goal achievement, and subjective norms toward AI-based learning.	MT1 - MT4 (Goal Achievement); Min3 - MinB4 (Interest); NS1 - NS6 (Subjective Norms).	Li, 2023	0.954	0.956	0.962	0.763
Behavioral Intention (BI) Likelihood of adopting and recommending AI-based learning systems.	Beln1 - Beln4: Intention to use and recommend AI for learning.	Li, 2023	0.932	0.945	0.952	0.833

The measurement model's reliability and validity were rigorously evaluated. Reliability was confirmed with Cronbach's Alpha, rho_A, and Composite Reliability (CR), all exceeding 0.7, indicating internal consistency, with Cronbach's Alpha values above 0.8 for strong reliability (Hair et al., 2017). Convergent validity was supported by Average Variance Extracted (AVE) values above 0.5, confirming that indicators accurately represent their constructs (Hair et al., 2019).

The structural model's predictive power was demonstrated by R-squared (R^2) values: perceived usefulness (0.763), perceived ease of use (0.561), learning motivation (0.848), behavioral intention (0.492), and attitude toward AI-based systems (0.558), reflecting moderate to high explanatory power. These metrics affirm the model's robustness, ensuring a strong foundation for hypothesis testing.

4.4 Data Collection

Primary data were collected via an online survey distributed through Google Forms, with links shared on WhatsApp Groups and Instagram to ensure accessibility among the target demographic. The survey was open for three weeks, from September 12 to October 4, 2024, allowing ample time for participant engagement.

Participants received information about the study's purpose, confidentiality assurances, and the voluntary nature of their participation. Secondary data were gathered from reputable sources, including academic journals and government reports, to provide contextual support and background for primary data interpretation. After data cleaning to remove duplicates and incomplete responses, the final sample comprised 166 valid entries.

4.5 Data Analysis

Data analysis combined descriptive and inferential statistics. Descriptive analysis using SPSS 25.0 summarized demographic data and response distributions, while hypothesis testing employed Structural Equation Modeling (SEM) with Partial Least Squares (PLS) in version 4.0, suited for exploratory studies and complex models (Sohaib & Han, 2023). The analysis included two stages: measurement model assessment, which evaluated reliability and validity through indicator loadings (≥ 0.7), Cronbach's Alpha, Composite Reliability, and AVE values, and structural model assessment, which tested hypothesized relationships using path coefficients, t-values, and R-squared values. This comprehensive approach confirms the robustness of the conceptual model and provides insights into the influence of communication channels, perceptions, attitudes, motivation, and behavioral intentions on AI adoption in entrepreneurial education.

5. Findings

5.1 Demographic Profile and Familiarity with AI in Entrepreneurship Education

The analysis of respondents' demographics and their familiarity with AI shows a predominantly young, tech-savvy group, with a significant portion (64.5%) aged 18-24. Most respondents (64.5%) are at least somewhat familiar with AI, with 55.4% already using AI tools in their education. While confidence in AI's potential for entrepreneurship is moderate to high (54.2% moderate, 30.1% high), half of the participants indicated a need for more understanding before fully adopting AI, suggesting a gap in readiness despite general awareness and interest in its benefits (Table 2).

5.2 Motivational Drivers, Barriers, and Learning Preferences for AI Adoption

Motivations for AI adoption in entrepreneurship highlight creativity (18.9%) and efficiency (18.7%) as major drivers, with respondents also valuing AI's ability to improve marketing (16%) and other operational aspects. Barriers include a lack of understanding (55.4%) and difficulty using AI (46.4%), signaling a need for clearer educational resources and user-friendly tools. A significant portion of respondents (40.9%) also expressed the need for structured training.

JOURNAL OF CONSUMER SCIENCES

In terms of learning preferences, interactive learning modules (63.3%) and practical video tutorials (48.2%) were most favored, suggesting a preference for hands-on, applied learning experiences. Key motivators for adoption include ease of use (66.3%) and relevance to business needs (57.2%), with institutional support also seen as important (45.2%) (Table 2).

5.3 Insights from the Design Thinking Process and Future Recommendations

The preferences for interactive, practical, and real-world project-based learning align with design thinking principles, emphasizing a human-centered, problem-solving approach. Future educational strategies should focus on providing accessible, relevant, and practical AI applications that directly address business needs. Integrating user-friendly technology interfaces, structured mentorship, and applied learning experiences are recommended to enhance AI adoption and support students in realizing AI's full potential in entrepreneurship (Table 2).

Table 2. Distribution of respondents by gender, age range, and understanding of the concept of artificial intelligence (AI) in the context of entrepreneurship learning

Variables	Total	Percentage	Insights from the Design Thinking Process
Gender			n/a
Male	65	39.2	
Female	101	60.8	
Age			n/a
18-24 years old	107	64.5	
25-34 years old	51	30.7	
35-44 years old	8	4.8	
Level of Familiarity with AI Concepts			n/a
Very unfamiliar	4	2.4	
Not familiar	55	33.1	
Familiar	64	38.6	
Very Familiar	43	25.9	
AI Usage Rate for Learning entrepreneurship			n/a
Never heard of or used AI	23	13.9	
Have heard of but have not used	51	30.7	
Already using and learning	92	55.4	
Level of confidence in the benefits of use			n/a
Not Sure	26	15.7	
Sure	90	54.2	
Very confident	50	30.1	
Readiness to adopt the use of AI applications			
Not ready	8	4.8	
Need to learn first	83	50.0	Simple training is required before being ready
Very ready	75	45.2	
Reasons for being interested in using AI			
Get creative ideas for product or service development	85	18.9	AI supports creativity in idea development
Improve efficiency and productivity in managing business	84	18.7	AI improves business efficiency and productivity
Improve marketing and branding strategies	72	16.0	Facilitate marketing and branding strategies
Manage projects and tasks more efficiently	62	13.8	
Improve sales and customer service strategies	58	12.9	
Improve content and writing quality	37	8.3	
Improve visual communication and presentation	33	7.4	
Strengthen the labor recruitment process	18	4.0	

JOURNAL OF
CONSUMER SCIENCES

Table 2. Distribution of respondents by gender, age range, and understanding of the concept of artificial intelligence (AI) in the context of entrepreneurship learning (Continue)

Variables	Total	Percentage	Insights from the Design Thinking Process
Major barriers faced in using AI			
Lack of understanding of how AI works	92	55.4	AI is considered difficult to understand by students
The perception that AI is difficult to use	77	46.4	Perceived difficulty in using AI is still a major obstacle
Lack of available training or guidance	68	40.9	Simple guidance or training is required
Uncertainty regarding the cost of AI implementation	43	25.9	AI implementation cost concerns
Concerns about data privacy and security	39	23.5	Privacy and data security concerns are a concern for students
The main problems faced by students related to AI			
Lack of understanding of technology	92	55.4	The biggest barrier is a low understanding of AI
Limited time to learn AI	64	38.6	Time constraints are also a common problem
Cost and access to AI technology	43	25.9	AI implementation cost is a significant concern
Factors that increase motivation to learn entrepreneurship through AI			
Ease of use of AI	110	66.3	The ease of use of AI motivates students to learn more
Direct relevance to the business	95	57.2	If AI is perceived as relevant to business needs, motivation increases
Support from institutions or mentors	75	45.2	Support from mentors or institutions is important to increase motivation
Clarity of direct benefits from AI	70	42.2	Students need to see the tangible benefits of AI to increase motivation
Lack of understanding of how AI works	92	55.4	AI is considered difficult to understand by students
The perception that AI is difficult to use	77	46.4	Perceived difficulty in using AI is still a major obstacle
Lack of available training or guidance	68	40.9	Simple guidance or training is required
Uncertainty regarding the cost of AI implementation	43	25.9	AI implementation cost concerns
Concerns about data privacy and security	39	23.5	Privacy and data security concerns are a concern for students
Preferences for the Ideal Form of Entrepreneurship Learning through AI			
Interactive learning module	105	63.3	Learning modules should be the primary focus
Practical video tutorials	80	48.2	Video tutorials as popular support
Real project-based case studies	75	45.2	Case studies with real projects are in high demand
Group discussion and question-and-answer	58	34.9	In-depth discussions and interactions are also required
Simulation of AI usage	53	31.9	Practical simulation of the use of AI is also considered important

Notes: n/a=not applicable

5.4 Outer Model Test Results

The outer model evaluation consists of three stages to ensure reliability and validity. First, model fit is assessed using indices from three categories: absolute (SRMR, RMSEA, GFI), incremental (AGFI, NFI, CFI, RFI), and parsimonious (PGFI). The model fit is deemed good, forming a solid foundation for further analysis.

Second, the measurement model fit is evaluated by validating indicators. Invalid indicators were removed, particularly those for learning motivation (SN1-SN6). Convergent validity, assessed via Average Variance Extracted (AVE), exceeded the threshold (>0.50), and construct reliability (CR) confirmed internal consistency, with all constructs surpassing the reliability threshold (>0.7).

JOURNAL OF
CONSUMER SCIENCES

Third, the structural model fit is tested by examining hypotheses through path coefficients and t-values in the SEM. All t-values exceeded 1.96, confirming statistically significant relationships. These findings validate the model's structural integrity, confirming the hypothesized relationships within the data. A visual representation in Figure 2 further supports the model's robustness.

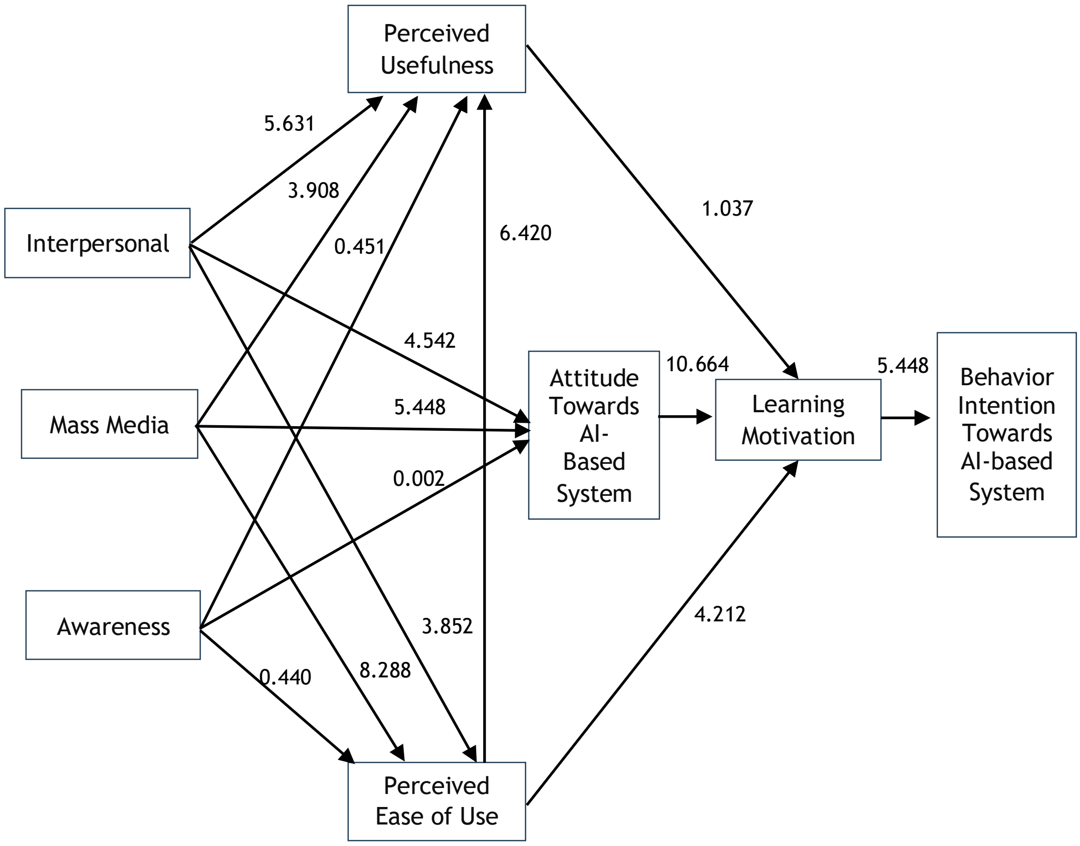

Figure 2. Measurement Model Test Results

5.5 Structural Model Test Results (Inner Model)

The structural model, also known as the inner model, was evaluated following the confirmation of an acceptable outer model. This inner model assessment was performed using key metrics within Smart-PLS, including the coefficient of determination (R^2) and the path coefficient or t-value. The R^2 values indicate the degree of variance explained by the independent variables for each endogenous variable. Specifically, the R^2 values for each variable are as follows: behavioral intention (0.368), attitude (0.560), learning motivation (0.874), perceived ease of use (0.561), and perceived usefulness (0.763). These values suggest a substantial amount of variance explained, particularly in learning motivation and perceived usefulness, underscoring the strength of the model.

The model's Goodness of Fit (GOF) was calculated using the Q^2 value, which was 0.9964, indicating excellent predictive capability. The significant R^2 values and high Q^2 confirm the model's robustness and relevance for research and practical applications. This study employed a one-tailed hypothesis approach, with a significance threshold t-value set at 1.96. Analysis in Smart-PLS revealed the following results: the first hypothesis (H1), which postulated that learning motivation—encompassing interest, goal attainment, and subjective norms—positively influences behavioral intention toward AI-based systems, was confirmed. This is evidenced by a path coefficient of 0.607 and a t-value of 8.986, demonstrating a substantial positive impact of learning motivation on the sintention to use AI. Similarly, the second hypothesis (H2), asserting that a positive attitude towards AI significantly enhances learning motivation, was validated with a path coefficient of

0.723 and a t-value of 10.664, further emphasizing the influence of attitudes on motivation.

In contrast, the third hypothesis (H3) was rejected, suggesting that perceived usefulness negatively impacts learning motivation. The data showed no significant effect, as indicated by a path coefficient of -0.076 and a t-value of 1.037. Conversely, hypothesis four (H4), relating to the positive effect of perceived ease of use on learning motivation, was accepted, with a path coefficient of 0.321 and a t-value of 4.212, underscoring that ease of use positively contributes to motivation.

Subsequent hypotheses five (H5) and six (H6), which propose that interpersonal communication and mass media positively affect attitudes toward AI-based systems, were both accepted. Interpersonal communication showed a path coefficient of 0.384 with a t-value of 4.542, while mass media demonstrated a path coefficient of 0.441 with a t-value of 5.448. These findings underscore the importance of communication channels in shaping attitudes toward AI. However, hypothesis seven (H7), which posited that awareness positively influences attitudes toward AI-based systems, was rejected (path coefficient = 0.000, t-value = 0.002), indicating no significant effect of awareness on attitudes. The results of the estimation of the direct effect of these variables on the Structural Equation Modeling (SEM) model are presented in detail in Table 3.

Table 3. Estimation results of direct effects on the SEM model

Pathway Variables	Path Coefficient	T-values	P-values	Conclusion
Learning Motivation -> Behavioral Intention Towards AI-based System	0.607	8.986	0.000*	Significant
Attitude Towards AI-based System -> Learning Motivation	0.723	10.664	0.000*	Significant
Perceived Usefulness -> Learning Motivation	-0.076	1.037	0.300	Insignificant
Perceived Ease of Use -> Learning Motivation	0.321	4.212	0.000*	Significant
Interpersonal -> Attitude towards AI-based System	0.384	4.542	0.000*	Significant
Mass Media -> Attitude towards AI-based System	0.441	5.448	0.000*	Significant
Awareness -> Attitude towards AI-based System	0.000	0.002	0.998	Insignificant
Interpersonal -> Perceived Usefulness	0.366	5.631	0.000*	Significant
Mass Media -> Perceived Usefulness	0.233	3.908	0.000*	Significant
Awareness -> Perceived Usefulness	-0.038	0.451	0.652	Insignificant
Interpersonal -> Perceived Ease of Use	0.287	3.852	0.000*	Significant
Mass Media -> Perceived Ease of Use	0.574	8.288	0.000*	Significant
Awareness -> Perceived Ease of Use	-0.053	0.440	0.660	Insignificant
Perceived to Use -> Perceived Usefulness	0.424	6.420	0.000*	Significant

Note: *significant at $p<0.05$

Hypotheses eight (H8) and nine (H9), asserting that interpersonal communication and mass media positively impact perceived usefulness, were confirmed, with respective path coefficients of 0.366 (t-value = 5.631) and 0.233 (t-value = 3.908). However, hypothesis ten (H10) on the effect of awareness on perceived usefulness was not supported (path coefficient = -0.038, t-value = 0.451). Similarly, hypotheses eleven (H11) and twelve (H12), which posit positive effects of interpersonal communication and mass media on perceived ease of use, were both accepted, as reflected in path coefficients of 0.287 (t-value = 3.852) and 0.574 (t-value = 8.288), respectively. Hypothesis thirteen (H13), which suggests a positive effect of awareness on perceived ease of use, was rejected (path coefficient = -0.053, t-value = 0.440), indicating that awareness does not significantly impact ease of use perceptions. Finally, hypothesis fourteen (H14), asserting that perceived ease of use positively affects perceived usefulness, was confirmed, as evidenced by a path coefficient of 0.424 and a t-value of 6.420.

5.6 SCAMPER Analysis Based on Design Thinking for AI Integration in Entrepreneurship Education

The SCAMPER analysis offers a structured approach to enhancing AI integration in entrepreneurship education by focusing on practical, hands-on learning tailored to student needs. By substituting traditional methods with AI-driven, interactive e-learning modules, students engage with dynamic content that adapts based on their progress, increasing engagement and retention. A four-week pilot with a small group of students demonstrated the platform’s effectiveness in maintaining interest and ensuring comprehension.

The "Combine" element integrates AI tutorials within business strategy modules, allowing students to use tools like predictive analytics in real-world case studies, enhancing their strategic decision-making skills. Success was measured by students' ability to apply AI insights in projects, which industry mentors assessed.

Adaptation is achieved by offering modules at varying difficulty levels, ensuring that content matches students’ expertise. Post-module surveys track students' skill progression, ensuring content alignment with their needs. The "Modify" element incorporates project-based learning, where students tackle business challenges using AI, with their progress monitored through feedback. This approach prepares students to apply AI skills in real-world settings.

The "Elimination" element streamlines theoretical content, prioritizing practical applications. Overly technical details are replaced with core principles and hands-on exercises, ensuring the curriculum remains accessible and relevant. Finally, the “Put to Another Use” element applies AI learning modules to simulate real-life startup challenges, allowing students to tackle sales forecasting and inventory management tasks. Performance is assessed by students' ability to complete these simulations successfully.

The SCAMPER-based curriculum design provides a comprehensive, hands-on approach to AI integration in entrepreneurship education. This approach ensures students are well-prepared for real-world challenges in AI-driven entrepreneurial environments by emphasizing practical applications and tailoring content to students' skill levels.

6. Discussion

6.1 Demographic Profile and Familiarity with AI in Entrepreneurship Education

This study provides key insights into the demographic distribution and engagement with AI in entrepreneurship education. The results highlight a predominance of female participants and a younger demographic, which suggests a favorable environment for AI adoption, as younger individuals tend to be more receptive to technological innovations

JOURNAL OF CONSUMER SCIENCES

(Apostu et al., 2024; Blanco-González et al., 2024; Bardales-Cárdenas et al., 2024; Syed et al., 2024). Many respondents reported moderate to high familiarity with AI, reflecting growing interest in its use in business contexts. However, a knowledge gap remains, with many respondents expressing needing more education before fully adopting AI. This finding aligns with existing literature, which suggests that while awareness of AI's benefits is increasing, practical implementation remains challenging (Radhakrishnan & Chattopadhyay, 2020). Educational institutions must focus on bridging this knowledge gap by developing interventions that improve students' understanding of AI technologies in entrepreneurship (AlGerafi et al., 2023).

6.2 Motivational Drivers, Barriers, and Learning Preferences for AI Adoption

The study identifies respondents' key motivations for AI adoption, focusing on fostering creativity in product development and enhancing business efficiency. This aligns with the findings by Wamba-Taguimdje et al. (2020) on AI's role in innovation and operational excellence. Motivations also include improvements in marketing, project management, and customer service, underscoring the diverse applications of AI in entrepreneurship (Ahmed & Ganapathy, 2021). Despite this enthusiasm, barriers such as a lack of understanding of AI functionalities and perceiving AI as challenging to use highlight the need for simplified educational resources and user-friendly tools (Davis et al., 1989). Additionally, the absence of accessible training programs underscores the importance of structured support for effective AI adoption (Chai et al., 2020). Respondents strongly preferred interactive learning, practical video tutorials, and project-based case studies, indicating a demand for applied, engagement-driven educational formats to bridge the gap between theory and real-world business challenges (Hermann, 2022).

6.3 Insights from the Design Thinking Process and Future Recommendations

The findings highlight the relevance of the design thinking approach in creating AI-based learning solutions tailored to entrepreneurship students' needs. The empathize stage is crucial for understanding barriers such as limited AI knowledge, time constraints, and concerns about costs and data security (Fabri, 2015). In the define stage, key issues include enhancing students' motivation and acceptance of AI, with ease of use and real-world relevance being central factors in encouraging engagement. Mentors and institutional support are also essential for building students' confidence in adopting AI. The ideate stage proposed interactive learning modules, video tutorials, and real-world project case studies as solutions to bridge the knowledge gap. In the prototype phase, the focus on user-friendly modules ensures accessibility for students from diverse backgrounds, with ongoing feedback allowing for continuous improvement.

6.4 Structural Model Test Results

The evaluation of the 14 hypotheses reveals intricate dynamics that impact students' intentions and attitudes toward AI technologies, emphasizing the multifaceted nature of these interactions.

6.4.1 Learning Motivation and Behavioral Intention Towards AI-Based Systems

The first hypothesis suggests that learning motivation significantly influences students' behavioral intentions toward AI adoption. Li (2023) affirms that students with higher intrinsic motivation, driven by personal interest and enjoyment, are likelier to engage with AI technologies. This motivation encourages exploration and enhances students' intentions to integrate AI into their learning practices. Rudhumbu (2022) supports this, showing that motivational factors, particularly learning motivation, are crucial in shaping

JOURNAL OF CONSUMER SCIENCES

students' intentions to adopt educational technologies in blended learning contexts. This aligns with Ajzen's (1991) Theory of Planned Behavior, which emphasizes the importance of motivation in influencing behavioral intentions.

6.4.2 Attitude towards AI-based and Learning Motivation

Similarly, the second hypothesis examines the positive relationship between students' attitudes toward AI-based systems and their learning motivation. Acquah et al. (2024) prove that students with favorable perceptions of AI technologies are more motivated to engage with these systems. Li (2023) further elaborates that when students view AI as valuable and beneficial to their education, their motivation to learn increases. This is reinforced by Hariyono (2024), who highlights that students' positive attitudes, influenced by social factors and perceived value, enhance learning motivation. Lee et al. (2022) emphasize the reciprocal relationship between attitudes and motivation, suggesting that promoting positive perceptions of AI can significantly improve students' learning engagement and outcomes.

6.4.3 Perceived Usefulness and Learning Motivation

Conversely, the third hypothesis explored the anticipated effect between perceived usefulness and learning motivation. However, the findings indicate a lack of significant effect, suggesting that motivation may be influenced more by factors such as personal relevance and ease of integration into academic contexts. While previous studies emphasize that perceived usefulness typically drives motivation, such as Dabbous and Boustani (2023), who found that perceived usefulness fosters engagement by linking learning with tangible benefits, and Rokhim et al. (2022), who highlighted its role in learning management systems during the COVID-19 pandemic, the current study diverges. It suggests that while perceived usefulness is important in many contexts, its effect on motivation may vary depending on the students' perception of AI's relevance to their personal learning goals. This points to motivation's complex, multifaceted nature in educational AI integration.

6.4.4 Perceived Ease and Learning Motivation

The fourth hypothesis examined the effect of perceived ease of use on learning motivation, revealing a significant positive relationship. This suggests that when AI technologies are user-friendly, students are more motivated to engage with them. Previous studies support this, such as Elkaseh et al. (2016), who found that usability is essential for encouraging engagement with educational technologies by reducing cognitive effort. Deshpande et al. (2024) demonstrated that ease of use in e-learning platforms boosts motivation, particularly when aligned with career objectives. Similarly, Nedeljković and Petrović (2023) highlighted the importance of user-friendly systems for student motivation during the pandemic. In AI-based learning systems, Li (2023) confirmed that ease of use encourages positive behavioral intentions, making students more likely to engage confidently with AI tools. These findings collectively underscore the critical role of ease of use in supporting motivation, particularly in educational settings where user-friendly experiences align with students' learning goals.

6.4.5 Interpersonal Communication on Attitude toward AI-based systems

The fifth hypothesis explored the effect of interpersonal communication on attitudes toward AI-based systems, confirming a strong connection between positive peer interactions and favorable attitudes toward AI. Frequent, meaningful exchanges within trusted networks facilitate sharing of insights and clarifications, increasing comfort and credibility regarding AI technologies (Byrd & Zhang, 2023). The data further reveal that network characteristics, such as tie strength and homophily, amplify this effect, as individuals are more receptive to favorable views on AI when conveyed by trusted peers (Chih et al., 2020). This aligns with the Cognitive-Affective-Behavioral (CAB) model, emphasizing how credible sources influence cognitive assessments, affective responses, and behavioral intentions. Additionally, shared cultural or academic contexts enhance the impact of interpersonal communication, reinforcing AI's desirability within cohesive networks (Wang, 2022). These findings highlight the importance of interpersonal communication in fostering positive attitudes toward AI, particularly in supportive and culturally or academically aligned networks.

6.4.6 Mass Media and Attitudes towards AI-based Systems

The sixth hypothesis examined the effect of mass media on attitudes toward AI-based systems, confirming that favorable media representations significantly influence the acceptability of AI technology. Media, especially when portraying AI through relatable narratives and credible endorsements, makes the technology more accessible and relevant to daily life (Uribe et al., 2022). The findings also emphasize the role of digital media platforms, mainly social media, in fostering interactive engagement with AI content. Transparent portrayals of AI on these platforms enhance perceived trustworthiness and credibility, addressing concerns related to ethics and data security (Lee & Chung, 2023). Furthermore, traditional media sources like television and newspapers continue to shape public opinion by reinforcing AI's safety and reliability. Together, these media forms contribute to a comprehensive public perception, highlighting the mass media's crucial role in shaping attitudes toward AI adoption.

6.4.7 Awareness and Attitude towards AI-based Systems

In contrast, the seventh hypothesis suggested that awareness positively influences attitudes toward AI-based systems. However, the results reveal a more complex relationship, showing that while awareness contributes to familiarity with AI, it does not independently foster positive attitudes. Awareness, when not accompanied by engagement or more profound understanding, has limited influence on shaping favorable perceptions (Chou et al., 2022). The findings emphasize that experiential learning, which combines awareness with practical exposure, is crucial for developing positive attitudes. This aligns with Radhakrishnan and Chattopadhyay (2020), who highlight that experience-based engagement enhances awareness and helps individuals grasp AI's practical applications and ethical implications. Deepa and Baral (2022) also note that structured, hands-on experiences are more effective in shaping attitudes than passive information. Therefore, the results suggest that awareness alone is insufficient for fostering positive perceptions, with practical exposure playing a key role in transforming familiarity into a deeper, more informed understanding of AI's utility and ethical viability.

6.4.8 Interpersonal Communication and Mass Media and Perceived Usefulness

The eighth and ninth hypotheses explored the influence of interpersonal communication and mass media on perceived usefulness, with the findings confirming both hypotheses. Interpersonal communication facilitates personalized, context-specific discussions that enhance the relevance of AI by addressing individual concerns, reducing uncertainties, and increasing perceived applicability (Shang et al., 2021). Such peer-driven interactions resonate with students' academic and professional goals, reinforcing the perceived usefulness of AI. In contrast, mass media provides a broader societal context for AI, amplifying its perceived utility through visual and narrative forms that reach a larger audience. Research suggests that media channels rich in content, such as video or

JOURNAL OF
CONSUMER SCIENCES

interactive formats, are particularly effective in illustrating AI's complex functionalities, making the technology more accessible and relatable (Yen, 2023). This aligns with Hsieh and Lee (2021), who found that exposure to AI's capabilities through media can enhance perceived usefulness by showcasing its versatility across various domains. Interpersonal communication and mass media create a layered effect on perceived usefulness. While peer interactions offer tailored insights that make AI relevant within students' immediate environments, media exposure provides broader societal validation, illustrating AI's practical applications in real-world contexts. This dual-channel influence strengthens students' perceptions of AI's usefulness, reinforcing its value personally and within a wider societal framework.

6.4.9 Awareness and Perceived Usefulness

The tenth hypothesis examined the effect of awareness on perceived usefulness, revealing a non-significant effect, which suggests that increased awareness alone does not lead to strong perceptions of AI's practical utility. This finding indicates that general awareness provides only an introductory understanding without connecting to specific practical applications. AlGerafi et al. (2023) note that while awareness offers a foundational overview, it often fails to translate into beliefs about usefulness without further engagement. Shin et al. (2024) emphasize that awareness is a broad knowledge framework, lacking the depth required to impact perceived usefulness. This distinction aligns with technology acceptance research, where perceived usefulness often develops when users engage with technology in ways that meet their personal needs and objectives (Deepa & Baral, 2022). Awareness alone does not provide the context to visualize how AI can serve specific roles in academic or professional settings. Yen (2023) supports this perspective, stating that perceived usefulness is strengthened when information is presented in real-life, applied contexts, making it easier for students to grasp AI's practical implications.

6.4.10 Interpersonal Communication and Mass Media and Perceived Ease of Use

The eleventh and twelfth hypotheses examined the effect of interpersonal communication and mass media on perceived ease of use, with both hypotheses showing significant positive effects. The findings suggest that interpersonal communication and media exposure are pivotal in shaping students' perceptions of AI's usability. Interpersonal communication offers a direct, personalized approach, where interactions with peers or mentors allow students to gain context-specific insights, reducing ambiguity about AI tools. This fosters a sense of familiarity and approachability, as students can ask questions and receive tailored feedback (Deepa & Baral, 2022). The social learning also enables students to observe AI in use, demystifying the technology and enhancing perceptions of its ease of use (Shang et al., 2021).

In contrast, mass media acts as a broad-reaching channel that complements interpersonal communication by presenting AI in diverse, relatable scenarios. Media representations, especially through visual and interactive content, help illustrate AI's functionalities, reducing perceived complexity. Platforms such as video tutorials and interactive guides make AI appear more intuitive and accessible. Chou et al. (2022) highlight that media-rich platforms increase perceived ease of use by offering practical, user-friendly narratives. This aligns with Hsieh and Lee's (2021) finding that high-engagement media, such as video and interactive content, reduce cognitive load and simplify initial interactions with technology. Interpersonal communication and mass media together form a multi-dimensional framework, where interpersonal communication offers personalized support, while mass media reinforces AI's societal relevance, boosting students' confidence in using AI tools (Yen, 2023).

6.4.11 Awareness and Perceived Ease of Use

The analysis indicates that awareness does not significantly affect perceived ease of use. Awareness provides only a basic understanding without the practical or experiential depth necessary to influence perceptions of ease of use (AlGerafi et al., 2023). This is supported by Mohr and Kühl (2021), who found that basic information about technology often leaves users with an abstract impression, failing to clarify how the technology can be applied in specific contexts.

Research on technology acceptance highlights that perceived ease of use typically requires active engagement or contextual relevance, which awareness alone cannot provide (Madjdian et al., 2024). Awareness campaigns may broaden general understanding, but without practical elements demonstrating real-world applications, they do not foster familiarity or comfort with the technology. Thus, awareness remains an introductory stage that is insufficient to shape perceptions of ease of use without adding interactive experiences or context-specific applications.

6.4.12 Perceived Ease of Use and Perceived Usefulness

Lastly, the fourteenth hypothesis proposed that perceived ease of use positively impacts perceived usefulness, consistent with Davis's (1989) Technology Acceptance Model (TAM), which posits that usability reduces the cognitive effort required to adopt technology, thereby enhancing its perceived value (AlGerafi et al., 2023). Students who find AI technologies user-friendly are more likely to view them as beneficial for learning and entrepreneurial activities.

Ease of use is a critical driver of perceived usefulness in technology adoption (Pipitwanichakarn & Wongtada, 2021). User-friendly designs lower both cognitive and practical barriers, enabling students to focus on exploring applications rather than overcoming operational difficulties (AlGerafi et al., 2023). This fosters positive perceptions of technology’s relevance and effectiveness (Deepa & Baral, 2022), while also reducing resistance and encouraging integration in contexts where initial hesitation may exist (Kim et al., 2023).

The SEM analysis highlights the dynamic interplay between perceived ease of use, motivation, and attitudes, demonstrating that usability fosters intrinsic motivation and positive perceptions of usefulness, which is vital for sustained engagement with AI in entrepreneurship education (Duffett & Maraule, 2024). Intuitive designs that reduce cognitive load promote immediate appreciation of AI’s value, encouraging deeper integration into students' entrepreneurial activities (Kalinić et al., 2020).

6.5 SCAMPER Analysis Based on Design Thinking for AI Integration in Entrepreneurship Education

The SCAMPER framework—Substitute, Combine, Adapt, Modify, Eliminate, and Put to Another Use—offers a practical strategy to integrate AI into entrepreneurship education, fostering innovation and relevance. Substitute encourages replacing static lectures with AI-driven, adaptive e-learning platforms that personalize content to individual learning styles, enhancing engagement and retention (Ahmed & Ganapathy, 2021). Combining AI tools with business curricula enables students to apply AI in practical contexts like market analysis and customer segmentation, while mentorship enhances real-world relevance (Ahmed & Ganapathy, 2021). Adapt involves tailoring content to student expertise levels, from foundational AI concepts to advanced applications, ensuring inclusivity and confidence-building (Chai et al., 2020). Modify emphasizes project-based learning, allowing students to design AI-driven solutions to business challenges and aligning education with industry demands (Dabbous & Boustani, 2023). Eliminate streamlines outdated content, prioritizing practical AI applications directly supporting entrepreneurial skills (Cautela et al., 2019). Finally, Put to Another Use employs AI tools in simulated startup scenarios, bridging theory and practice while preparing students for real-world challenges (Flavián et al., 2022). This structured approach ensures that AI integration remains student-centered, relevant, and aligned with modern entrepreneurial needs.

6.6 Managerial Implications

The findings of this study provide actionable insights for educational institutions, policymakers, and stakeholders in entrepreneurship education. As AI technologies become critical for innovation, curricula must integrate AI tools effectively while addressing identified barriers. Institutions should design practical, AI-focused learning experiences that align with entrepreneurial objectives, such as project-based activities to apply AI tools in real-world scenarios, fostering deeper engagement and retention (Ahmed & Ganapathy, 2021).

To address barriers, institutions must provide structured training and workshops to enhance students' confidence in using AI. Investments in user-friendly technologies can further promote accessibility, ensuring adoption across diverse technical backgrounds (Elkaseh et al., 2016). Supportive environments, including mentorship programs with industry experts, can bridge the gap between theoretical knowledge and practical application, positively influencing perceptions of AI (Chou et al., 2022). Peer collaboration through group projects and discussions can also improve attitudes toward AI, fostering a culture of shared learning and innovation (Kutter et al., 2011).

Finally, providing practical exposure through internships, partnerships, and real-world projects will enhance students' ability to utilize AI effectively in entrepreneurial contexts. This approach aligns with the importance of ease of use and perceived utility in technology adoption, ensuring students are well-prepared for AI-driven entrepreneurial challenges (Dabbous & Boustani, 2023). These strategies collectively emphasize the need for a holistic, hands-on approach to integrating AI into entrepreneurship education.

6.7 Theoretical Contribution

This research makes a substantial theoretical contribution to understanding AI adoption in education by integrating three frameworks: the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and Design Thinking. These frameworks offer a holistic perspective on developing educational interventions to enhance AI adoption in entrepreneurship education.

The TPB highlights the influence of intrinsic motivation on behavioral intentions, emphasizing that attitudes, subjective norms, and perceived behavioral control shape students' intentions (Ajzen, 1991). This study reinforces TPB by demonstrating how positive attitudes toward AI, driven by engagement and practical relevance, significantly motivate students to adopt these technologies. Addressing motivational factors in curricula is essential for fostering successful AI adoption.

The TAM framework complements this perspective by focusing on perceived ease of use and usefulness (Davis, 1989). Findings confirm that ease of use positively influences students' motivation and intention to adopt AI. This research strengthens the theoretical

JOURNAL OF
CONSUMER SCIENCES

foundation for TAM's application in fostering AI acceptance in entrepreneurship education by connecting these constructs to the educational context.

Integrating Design Thinking further enriches this framework by emphasizing empathy, ideation, and prototyping in curriculum development. Through SCAMPER analysis, this study demonstrates how educators can iteratively adapt learning experiences to meet students' needs, ensuring practical relevance and real-world problem-solving (Fabri, 2015; Corrales-Estrada, 2020; Lee & Park, 2021). This user-centered approach aligns with the demand for dynamic, application-focused educational practices.

6.8 Limitations

Several limitations must be acknowledged. One significant limitation is the use of non-probability sampling methods, which may impact the representativeness of the findings. As a result, the study's outcomes may not fully capture the diversity and variation within the broader population of students. This limitation constrains the generalizability of the findings and suggests that caution should be exercised when applying these results to different contexts or populations. Future research should consider employing probability sampling techniques to enhance the representativeness and robustness of the findings, thereby allowing for more comprehensive conclusions regarding AI adoption in educational settings.

7. Conclusions

This study investigates the adoption of artificial intelligence (AI) technologies in entrepreneurship education, uncovering key factors that shape students' engagement with AI. The analysis reveals that most respondents were female and aged between 18 and 24, with a moderate to high understanding of AI concepts. A significant portion of the respondents had used or studied AI applications in business or entrepreneurship contexts. Despite recognizing the benefits of AI for entrepreneurship development, many students felt they needed a deeper understanding before fully adopting AI in their learning processes.

The findings emphasize that intrinsic motivation, positive attitudes toward AI, and perceived ease of use are crucial drivers of students' intentions to adopt AI technologies. Students were primarily motivated to use AI for generating creative ideas in product or service development and improving efficiency and productivity in business management. They also viewed AI as beneficial for optimizing marketing strategies, managing tasks, improving sales, enhancing customer service, and refining content quality.

Structural analysis reveals that learning motivation positively influences students' behavioral intentions to adopt AI-based systems. Students' attitudes toward AI also significantly impact their motivation. While perceived usefulness did not directly influence motivation, perceived ease of use had a strong positive effect. Interpersonal interactions and mass media played a significant role in shaping positive attitudes toward AI and perceived usefulness, although awareness alone did not significantly influence these variables. Additionally, perceived ease of use positively affected perceived usefulness.

The SCAMPER analysis within the Design Thinking framework provides valuable strategies for integrating AI into entrepreneurship education. By leveraging the SCAMPER elements—Substitute, Combine, Adapt, Modify, Eliminate, and Put to Another Use—educators can design innovative, engaging learning modules tailored to students' needs, facilitating a deeper understanding of AI applications. This iterative approach promotes

JOURNAL OF
CONSUMER SCIENCES

continuous improvement, allowing educators to refine teaching strategies based on student feedback and engagement.

8. Recommendation

Based on these findings, several recommendations are made to guide future research. First, employing probability sampling techniques can improve the representativeness of results, offering a more accurate reflection of student diversity and their attitudes toward AI. Second, longitudinal studies should be conducted to capture changes in students' motivations and AI adoption over time, providing insights into the long-term impact of educational interventions. Third, exploring contextual factors across different educational settings through comparative studies can identify unique challenges and opportunities, informing curriculum design and policy development.

Additionally, future research could expand by examining variables like cultural influences, prior technological exposure, and institutional support systems to gain a more comprehensive understanding of AI adoption. Investigating students' decision-making processes, preferences, and behavior patterns would offer valuable insights for developing targeted strategies. Lastly, evaluating the integration and usability of emerging AI tools in education will provide actionable recommendations for educators and policymakers. By addressing these areas, future research can deepen the understanding of AI adoption in education and support the development of strategies that prepare students for an AI-driven entrepreneurial landscape.

Citation information
Cite this article as:
Wahpiyudin, C. A. B., Muhammadan, S. A., Amalia, A., Chrisanta, A., & Taryana, A. (2025). Determining AI-based learning adoption model for students in entrepreneurship education: a design thinking approach. *Journal of Consumer Sciences, 10*(1), 27-58. https://doi.org/10.29244/jcs.10.1.27-58

References

Acquah, B. Y. S., Arthur, F., Salifu, I., Quayson, E., & Nortey, S. A. (2024). Preservice Teachers' Behavioral Intention to Use Artificial Intelligence in Lesson Planning: A Dual-Staged PLS-SEM-ANN Approach. *Computers and Education: Artificial Intelligence*, *7*, 100307. https://doi.org/10.1016/j.caeai.2024.100307

Ahmed, A. A. A., & Ganapathy, A. (2021). Creation of automated content with embedded artificial intelligence: a study on learning management system for educational entrepreneurship. *Academy of Entrepreneurship Journal*, *27*(3), 1-10. https://search.proquest.com/openview/03fefb391067ddf46d9d5681b80f9ea6/1?pq-origsite=gscholar&cbl=29726

Alharbi, A., & Alzahrani, A. (2023). The influence of media on students' perceptions of artificial intelligence: A qualitative study. *Computers & Education*, 203, 104032. https://doi.org/10.1016/j.compedu.2023.104032

Almulla, M. A. (2024). Investigating Influencing Factors of Learning Satisfaction in AI ChatGPT for Research: University Students Perspective. *Heliyon*, *10*(11), e32220. https://doi.org/10.1016/j.heliyon.2024.e32220

Andini, T. P., Adawiyah, R., & Indriani, Y. (2023). Attitudes, decision making and purchasing patterns of online vegetable consumers. *Journal of Consumer Sciences*, *8*(3), 296-317. https://doi.org/10.29244/jcs.8.3.296-317

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action control* (pp. 11–39). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

AlGerafi, M. A., Zhou, Y., Alfadda, H., & Wijaya, T. T. (2023). Understanding the factors influencing higher education students' intention to adopt artificial intelligence-based robots. *IEEE Access, 12*, 152812-152824. Retrieved from https://ieeexplore.ieee.org/abstract/document/10247529/citations

Apostu, S. A., Mukli, L., Panait, M., Gigauri, I., & Hysa, E. (2022). Economic growth through the lenses of education, entrepreneurship, and innovation. *Administrative Sciences*, *12*(3), 74. https://doi.org/10.3390/admsci12030074

Baker, R. S., & Inventado, P. S. (2023). The role of technology in education: Bridging the gap between students and artificial intelligence. *Educational Technology Research and Development*, 71(2), 345-367. https://doi.org/10.1007/s11423-022-10123-4

Barua, B., & Urme, U. N. (2023). Assessing the online teaching readiness of faculty members. *Journal of Research in Innovative Teaching & Learning*, *11*(2), 1926-1945. https://doi.org/10.1108/JRIT-10-2022-0070.

Blanco-González, A., García, M. L. S., Cachón-Rodríguez, G., & Nistal, A. G. (2024). Research in business education. Connecting research with the educational challenges of universities. *Journal of Management and Business Education*, *7*(3), 379-395. https://doi.org/10.35564/jmbe.2024.0021

Bardales-Cárdenas, M., Cervantes-Ramón, E. F., Gonzales-Figueroa, I. K., & Farro-Ruiz, L. M. (2024). Entrepreneurship skills in university students to improve local economic development. *Journal of Innovation and Entrepreneurship*, *13*(1), 55. https://doi.org/10.1186/s13731-024-00408-1

Bowden, J., & Mirzaei, A. (2021). Consumer engagement within retail communication channels: An examination of online brand communities and digital content marketing initiatives. *European Journal of Marketing, 55*(5), 1411-1439. https://doi.org/10.1108/EJM-01-2018-0007

Byrd, G. A., & Zhang, Y. B. (2023). Communication frequency, identity accommodation, and attitudes toward people with disabilities in the United States: Disability salience and intergroup anxiety. *Language Sciences, 99*, 101564. https://doi.org/10.1016/j.langsci.2023.101564

Cardoso, P. R., Jolluskin, G., Paz, L., Fonseca, M. J., & Silva, I. (2023). Effects of awareness campaigns against domestic violence: Perceived efficacy, adopted behavior, and word of mouth. *Journal of Criminological Research, Policy and Practice, 9*(3/4), 177-192. https://doi.org/10.1108/JCRPP-11-2022-0057

Cautela, C., Mortati, M., Dell'Era, C., & Gastaldi, L. (2019). The impact of artificial intelligence on design thinking practice: Insights from the ecosystem of startups. *Strategic Design Research Journal, 12*(1), 114-134. https://doi.org/10.4013/sdrj.2019.121.08

Chai, C. S., Wang, X., & Xu, C. (2020). An extended theory of planned behavior for the modeling of Chinese secondary school students' intention to learn artificial intelligence. *Mathematics, 8*(11), 2089. https://doi.org/10.3390/math8112089

Chih, W. H., Hsu, L. C., & Ortiz, J. (2020). The antecedents and consequences of the perceived positive eWOM review credibility. *Industrial Management & Data Systems, 120*(6), 1217–1243. https://doi.org/10.1108/IMDS-10-2019-0573

Chou, C. M., Shen, T. C., Shen, T. C., & Shen, C. H. (2022). Influencing factors on students' learning effectiveness of AI-based technology application: Mediation variable of the human-computer interaction experience. *Education and Information Technologies, 27*(6), 8723-8750. https://doi.org/10.1007/s10639-021-10866-9

Chou, S. F., Liu, C.H. S., & Lin, J.Y. (2022). Critical criteria for enhancing consumption intention in restaurants during COVID-19. *British Food Journal, 124*(10), 3094-3115. https://doi.org/10.1108/BFJ-05-2021-0532

Corrales-Estrada, M. (2020). Design thinkers' profiles and design thinking solutions. *Academia Revista Latinoamericana de Administración*, *33*(1), 9-24. https://doi.org/10.1108/ARLA-01-2018-0028

Crudu, R. (2019). The role of innovative entrepreneurship in the economic development of EU member countries. *Journal of Entrepreneurship, Management and Innovation, 15*(1), 35-60. https://doi.org/10.7341/20191512

Cummings, J. J., & Ingber, A. S. (2024). Distinguishing social virtual reality: Comparing communication channels across perceived social affordances, privacy, and trust. *Computers in Human Behavior, 161*, 108427. https://doi.org/10.1016/j.chb.2024.108427

Dabbous, A., & Boustani, N. M. (2023). Digital explosion and entrepreneurship education: Impact on promoting entrepreneurial intention for business students. *Journal of Risk and Financial Management, 16*(1), 27. https://doi.org/10.3390/jrfm16010027

Davis, F. D. (1989). Mobile Money: décryptage d'une succes story africaine Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of two theoretical models. *Management Science, 35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Deepa, R., & Baral, R. (2022). Is my employee still attracted to me? Understanding the impact of integrated communication and choice of communication channels on employee attraction. *Corporate Communications: An International Journal, 27*(1), 110-126. https://doi.org/10.1108/CCIJ-09-2020-0136

Deshpande, A., Raut, R., Gupta, K., Mittal, A., Raheja, D., & Ekbote, N. (2024). Predictors of continued intention of working professionals for pursuing e-learning courses for career advancement. *Information Discovery and Delivery*, *52*(2), 175-184. https://doi.org/10.1108/IDD-11-2022-0120

Dong, X., Chang, Y., Wang, Y., & Yan, J. (2017). Understanding usage of Internet of Things (IOT) systems in China: Cognitive experience and affect experience as moderator. *Information Technology & People*, *30*(1), 117-138. https://doi.org/10.1108/ITP-11-2015-0272.

Duffett, R. G., & Maraule, M. (2023). Customer engagement and intention to purchase attitudes of Generation Z consumers toward emojis in digital marketing communications. *Young Consumers*, *25*(5), 607-624. https://doi.org/10.1108/YC-08-2023-1817

Dzidzornu, E., Angmorterh, S. K., Aboagye, S., Angaag, N. A., Agyemang, P. N., & Edwin, F. (2024). Communication channels of breast cancer screening awareness campaigns among women presenting for mammography in Ghana. *Journal of the American College of Radiology*, *21*, 1201-1207. https://doi.org/10.1016/j.jacr.2024.04.005

Elkaseh, A. M., Wong, K. W., & Fung, C. C. (2016). Perceived ease of use and perceived usefulness of social media for e-learning in Libyan higher education: A structural equation modeling analysis. *International Journal of Information and Education Technology, 6*(3), 192. Retrieved from https://www.ijiet.org/show-64-767-1.html

Fabri, M. (2015). Thinking with a new purpose: Lessons learned from teaching design thinking skills to creative technology students. *Lecture Notes in Computer Science*, *9186*, 32-43. https://doi.org/10.1007/978-3-319-20886-2_4

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services-the effect of technology readiness and awareness. *Journal of Service Management, 33*(2), 293-320. https://doi.org/10.1108/JOSM-10-2020-0378

Galvão, A., Marques, C., & Ferreira, J. J. (2020). The role of entrepreneurship education and training programmes in advancing entrepreneurial skills and new ventures. *European Journal of Training and Development*, *44*(6/7), 595-614. https://doi.org/10.1108/EJTD-10-2019-0174

Gonzalez, C., & de la Torre, J. (2020). The impact of educational videos on students' attitudes towards artificial intelligence. *Computers in Human Behavior*, 107, 106287. https://doi.org/10.1016/j.chb.2020.106287

Gupta, K. P. (2020). Investigating the adoption of MOOCs in a developing country: Application of technology-user-environment framework and self-determination theory. *Interactive Technology and Smart Education*, *17*(4), 355–375. https://doi.org/10.1108/ITSE-06-2019-0033

Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A human-machine communication research agenda. *New Media & Society, 22*(1), 70-86. https://doi.org/10.1177/1461444819858691

Hagger, A., Martin, S., & Mike, W. (2022). This is a self-archived version of an original article. This version may differ from the original in pagination and typographic details. *41*, 155-167. https://doi.org/10.1037/hea0001153

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2019). Multivariate data analysis. Cengage learning. *Hampshire, United Kingdom*, *633*.

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis, 1*(2), 107. https://doi.org/10.1504/ijmda.2017.10008574

Hariyono, H. (2024). Building a Future Generation of Entrepreneurs: An Experimental Study of the Integration of PBL and AI in Entrepreneurial. *EDUTEC: Journal of Education And Technology*, *7*(4), 444-453. https://doi.org/10.29062/edu.v7i4.921

Hermann, E. (2022). Artificial intelligence and mass personalization of communication content-An ethical and literacy perspective. *New Media & Society, 24*(5), 1258-1277. https://doi.org/10.1177/14614448211022702

Heryani, N., Sulistyaniningsih, E., Susilawati, S., & Tukiran, M. (2023). Pengaruh self efficacy dan literasi technopreneurship terhadap minat wirausaha mahasiswa prodi pendidikan ekonomi unindra. *Research and Development Journal of Education*, 9(1), 188. https://doi.org/10.30998/rdje.v9i1.15052

Horowitz, M. C., Kahn, L., Macdonald, J., & Schneider, J. (2024). Adopting AI: how familiarity breeds both trust and contempt. *AI & society*, *39*(4), 1721-1735. Retrieved from https://link.springer.com/article/10.1007/s00146-023-01666-5

Hsieh, S. H., & Lee, C. T. (2021). Hey Alexa: Examining the effect of perceived socialness in usage intentions of AI assistant-enabled smart speakers. *Journal of Research in Interactive Marketing, 15*(2), 267-294. https://doi.org/10.1108/JRIM-11-2019-0179

Hubert, M., Blut, M., Brock, C., Zhang, R. W., Koch, V., & Riedl, R. (2019). The influence of acceptance and adoption drivers on smart home usage. *European Journal of Marketing, 53*(6), 1073-1098. doi/10.1108/EJM-12-2016-0794/full/html

Ivanov, S., Soliman, M., Tuomi, A., Alkathiri, N. A., & Al-Alawi, A. N. (2024). Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. *Technology in Society*, *77*, 102521. https://doi.org/10.1016/j.techsoc.2024.102521

Kalinić, Z., Liébana-Cabanillas, F. J., Muñoz-Leiva, F., & Marinković, V. (2020). The moderating impact of gender on the acceptance of peer-to-peer mobile payment systems. *International Journal of Bank Marketing*, *38*(1), 138-158. https://doi.org/10.1108/IJBM-01-2019-0012

Karletsos, D., Hutchinson, P., Leyton, A., & Meekers, D. (2021). The effect of interpersonal communication in tobacco control campaigns: A longitudinal mediation analysis of a Ghanaian adolescent population. *Preventive Medicine, 142*, 106373. https://doi.org/10.1016/j.ypmed.2020.106373

Kim, J., Hardin, A., & Lee, S. (2023). Factors influencing resistance to hospitality information system change. *Journal of Hospitality and Tourism Insights*, *6*(5), 1926-1945. https://doi.org/10.1108/JHTI-04-2022-0129

Kshetri, N. (2021). The role of artificial intelligence in promoting financial inclusion in developing countries. *Journal of Global Information Technology Management*, *24*(1), 1-6. https://doi.org/10.1080/1097198X.2021.1871273

Kumar, V., & Singh, R. (2022). Awareness campaigns on artificial intelligence: Effects on students' perceptions and adoption. *International Journal of Information Management*, 62, 102427. https://doi.org/10.1016/j.ijinfomgt.2021.102427

Labrague, L. J., Aguilar-Rosales, R., Yboa, B. C., & Sabio, J. B. (2023). Factors influencing student nurses' readiness to adopt artificial intelligence (AI) in their studies and their perceived barriers to accessing AI technology: A cross-sectional study. *Nurse Education Today, 130*, 105945. https://doi.org/10.1016/j.nedt.2023.105945

Lee, A., & Chung, T.-L. D. (2023). Transparency in corporate social responsibility communication on social media. *International Journal of Retail & Distribution Management, 51*(5), 590-610. https://doi.org/10.1108/IJRDM-01-2022-0038

Lee, Y. F., Hwang, G. J., & Chen, P. Y. (2022). Impacts of an AI-based chatbot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation. *Educational Technology Research and Development*, *70*(5), 1843-1865. Retrieved from https://oa.mg/work/10.1007/s11423-022-10142-8

Lee, H. K., & Park, J. E. (2021). Designing a new empathy-oriented prototyping toolkit for the design thinking process: Creativity and design sensibility. *International Journal of Art & Design Education*, *40*(3), 524-536. https://doi.org/10.1111/jade.12345

Lestari, R. (2023). Impact of Entrepreneurship Education for Students in the Era of Globalization. *Saskara Indonesian Journal of Society Studies*, 3(2), 79-94. https://doi.org/10.21009/saskara.032.05

Li, K. (2023). Determinants of college students' actual use of AI-based systems: An extension of the technology acceptance model. *Sustainability, 15*(6), 5221. https://doi.org/10.3390/su15065221

Madjdian, D. S., van Asseldonk, M., Talsma, E. F., Amenu, K., Gemeda, B. A., Girma, S., Roesel, K., Grace, D., & Knight-Jones, T. J. D. (2024). Impact of a mass-media consumer awareness campaign on food safety behavior and behavioral determinants among women in Dire Dawa and Harar, Ethiopia. *Food Control, 163*, 110509. https://doi.org/10.1016/j.foodcont.2024.110509

Mafe, C. R., & Blas, J. (2010). A comparative study of mobile messaging services acceptance to participate in television programs. *Journal of Service Management*, *21*(1), 69-102. https://doi.org/10.1108/09564231011025128.

Mannan, S., Nordin, S. M., Rafik-Galea, S., & Rizal, A. R. A. (2017). The ironies of new innovation and the sunset industry: Diffusion and adoption. *Journal of Rural Studies, 55*, 316-322. https://doi.org/10.1016/j.jrurstud.2017.07.015

Miller, J. D., & Hwang, J. (2022). Simplifying artificial intelligence: How relatable content can enhance student engagement. *Journal of Educational Computing Research*, 60(5), 1025-1045. https://doi.org/10.1177/07356331211012345

Mirra, G., & Pugnale, A. (2022). Expertise, playfulness and analogical reasoning: three strategies to train Artificial Intelligence for design applications. *Springer Nature*, 2(1), 111-127. https://doi.org/10.1007/s44150-022-00035-y

Mohr, S., & Kühl, R. (2021). Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture,* *22*(6), 1816-1844. https://doi.org/10.1007/s11119-021-09814-x

Nabi, G., Liñán, F., Fayolle, A., Krueger, N., & Walmsley, A. (2017). The impact of entrepreneurship education in higher education: A systematic review and research agenda. *Academy of Management Learning & Education, 16*(2), 277-299. https://doi.org/10.5465/amle.2015.0026

Nedeljković, I., & Petrović, D. R. (2023). Student satisfaction and intention to use e-learning during the Covid-19 pandemic. *International Journal of Information and Learning Technology*, *40*(3), 225–241. https://doi.org/10.1108/IJILT-05-2022-0119

Nguyen, T. M., & Malik, A. (2022). Employee acceptance of online platforms for knowledge sharing: Exploring differences in usage behaviour. *Journal of Knowledge Management*, *26*(8), 1985–2006. https://doi.org/10.1108/JKM-06-2021-0420

Pipitwanichakarn, T., & Wongtada, N. (2021). Leveraging the technology acceptance model for mobile commerce adoption under distinct stages of adoption: A case of micro businesses. *Asia Pacific Journal of Marketing and Logistics*, *33*(6), 1415-1436. https://doi.org/10.1108/APJML-10-2018-0448.

Prasetiawan, A., Sunarto, S., & Estuti, E. (2021). Assesment potensi diri sebagai wirausaha mahasiswa. *Peningkatan Kinerja Berbasis Pada Kualitas Komunikasi Kepercayaan Dan Kerjasama Tim*, 3(2), 229-241. https://doi.org/10.33747/capital.v3i2.131

Primandaru, N. (2017). The Factors Affecting the Entrepreneurial Intention of College Students. *Jurnal Economia*, 13(1), 68. https://doi.org/10.21831/economia.v13i1.13276

Putri, P. T., & Simanjuntak, M. (2020). The role of motivation, locus of control and financial literacy on women investment decisions across generations. *Journal of Consumer Sciences*, *5*(2), 102-123. https://doi.org/10.29244/jcs.5.2.102-123

Radhakrishnan, J., & Chattopadhyay, M. (2020). Determinants and barriers of artificial intelligence adoption–A literature review. In *Re-imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation: IFIP WG 8.6 International Conference on Transfer and Diffusion of IT, TDIT 2020, Tiruchirappalli, India, December 18–19, 2020, Proceedings, Part I* (pp. 89-99). Springer International Publishing.https://link.springer.com/chapter/10.1007/978-3-030-64849-7_9

Rokhim, R., Mayasari, I., Wulandari, P., & Haryanto, H. C. (2022). Analysis of the extrinsic and intrinsic aspects of the technology acceptance model associated with the learning management system during the COVID-19 pandemic. *VINE Journal of Information and Knowledge Management Systems*, *52*(4), 312–340. https://doi.org/10.1108/VJIKMS-04-2022-0113

Roy, R., Babakerkhell, M. D., Mukherjee, S., Pal, D., & Funilkul, S. (2022). Evaluating the intention for the adoption of artificial intelligence-based robots in the university to educate the students. *IEEE Access, 10*, 125666-125678. doi: 10.1109/ACCESS.2022.3225555.

Rudhumbu, N. (2022). Applying the UTAUT2 to Predict the Acceptance of Blended Learning by University Students. *Asian Association of Open Universities Journal*, *17*(1), 15-36. https://doi.org/10.1108/AAOUJ-08-2021-0084

Rusu, V. D., & Roman, A. (2022). Smes Under the Umbrella of Covid-19 Pandemic: Changes and Challenges. *Finance, Economics and Tourism-FET 2022*, *22*, 119. Retrieved from https://www.researchgate.net/profile/Emmanuel-Mensah-15/publication/370025688

Rusu, V. D., Roman, A., & Tudose, M. B. (2022). Determinants of entrepreneurial intentions of youth: the role of access to finance. *Engineering Economics, 33*(1), 86-102. https://doi.org/10.5755/j01.ee.33.1.28716

Sagar, G., Anand, B., Perumalla Varalaxmi, A. S., & Raj, S. (2023). The role of entrepreneurship in economic growth and development. *Journal of Survey in Fisheries Sciences, 10*(1), 5940-5955. Retrieved from https://sifisheriessciences.com/journal/index.php/journal/article/view/2022

Saputra, A. D., Rahmatia, A., & Muslimah, M. (2021). How personal factors grow students' interest in entrepreneurship. *Journal of Services Management and Marketing, 14*(1), 61-76. Retrieved from https://www.e-journal.trisakti.ac.id/index.php/jasa/article/download/8336/6508

Sari, A., & Hairunisya, H. (2022). Pengaruh metode mengajar dosen dan perilaku belajar mahasiswa terhadap minat berwirausaha mahasiswa Universitas Bhinneka PGRI. *Jurnal Economina*, 1(3), 427-438. https://doi.org/10.55681/economina.v1i3.99

Sayaf, A. M., Alamri, M. M., Alqahtani, M. A., & Alrahmi, W. M. (2022). Factors influencing university students' adoption of digital learning technology in teaching and learning. *Sustainability, 14*(1), 493. https://doi.org/10.3390/su14010493

Shah, Z., & Wei, L. (2022). Interpersonal risk communication matters more than media risk communication in its impact on individuals' trust and preventive behaviors during COVID-19. *International Journal of Disaster Risk Reduction, 82*, 103369. https://doi.org/10.1016/j.ijdrr.2022.103369

Shang, L., Zhou, J., & Zuo, M. (2021). Understanding older adults' intention to share health information on social media: The role of health belief and information processing. *Internet Research, 31*(1), 100-122. https://doi.org/10.1108/INTR-12-2019-0512

Simamora, T. P., & Djamaludin, M. D. (2020). Analysis of intention to buy cinema e-tickets among IPB students with Theory of Planned Behavior (TPB) approach. *Journal of Consumer Sciences*, *5*(1), 58-72. https://doi.org/10.29244/jcs.5.1.58-72

Sicilia, M., & Palazón, M. (2023). Developing customer engagement through communication consistency and channel coordination. *Spanish Journal of Marketing - ESIC, 27*(2), 241-260. https://doi.org/10.1108/SJME-02-2022-0022

Sohaib, M., & Han, H. (2023). Building value co-creation with social media marketing, brand trust, and brand loyalty. *Journal of Retailing and Consumer Services, 74*, 103442. https://doi.org/10.1016/j.jretconser.2023.103442

Singh, S., Sahni, M. M., & Kovid, R. K. (2020). What drives FinTech adoption? A multi-method evaluation using an adapted technology acceptance model. *Management Decision*, *58*(8), 1675-1697. https://doi.org/10.1108/MD-09-2019-1318.

Stocchi, L., Michaelidou, N., & Micevski, M. (2019). Drivers and outcomes of branded mobile app usage intention. *Journal of Product & Brand Management*, *28*(1), 28-49. https://doi.org/10.1108/JPBM-02-2017-1436.

Syed, R. T., Tariq, U., Arnaut, M., & Agrawal, R. (2024). Entrepreneurship educator: a vital cog in the wheel of entrepreneurship education and development in universities. *Journal of Innovation and Entrepreneurship*, *13*(1), 66. https://doi.org/10.1186/s13731-024-00433-0

Tang, T., Li, P., & Tang, Q. (2022). New Strategies and Practices of Design Education Under the Background of Artificial Intelligence Technology: Online Animation Design Studio. *Frontiers Media*, *13*, 767295. https://doi.org/10.3389/fpsyg.2022.767295

Tran, H. T. T., & Corner, J. (2016). The impact of communication channels on mobile banking adoption. *International Journal of Bank Marketing, 34*(1), 78-109. https://doi.org/10.1108/IJBM-06-2014-0073

Uribe, R., Buzeta, C., Manzur, E., & Celis, M. (2022). Celebrity endorsement using different types of new media and advertising formats. *Academia Revista Latinoamericana de Administración,* *35*(3), 281-302. https://doi.org/10.1108/ARLA-08-2021-0167

Vocke, C., Constantinescu, C., & Popescu, D. (2019). Application potentials of artificial intelligence for the design of innovation processes. *Procedia CIRP*, *84*, 810-813. https://doi.org/10.1016/j.procir.2019.04.230

Wamba-Taguimdje, S. L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of

JOURNAL OF
CONSUMER SCIENCES

AI-based transformation projects. *Business process management journal*, *26*(7), 1893-1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wang, X. (2022). Attitudes toward COVID-19 vaccines and vaccine uptake intent in China: The role of collectivism, interpersonal communication, and the use of news and information websites. *Current Research in Ecological and Social Psychology, 3*, 100065. https://doi.org/10.1016/j.cresp.2022.100065

Winkler, C., Hammoda, B., Noyes, E., & Van Gelderen, M. (2023). Entrepreneurship education at the dawn of generative artificial intelligence. *Entrepreneurship Education and Pedagogy,* *6*(4), 579-589. https://doi.org/10.1177/25151274231198799

Yen, Y.-S. (2023). Channel integration affects usage intention in food delivery platform services: The mediating effect of perceived value. *Asia Pacific Journal of Marketing and Logistics, 35*(1), 54-73. https://doi.org/10.1108/APJML-05-2021-0372

Zhou, X., Van Brummelen, J., & Lin, P. (2020). Designing AI learning experiences for K-12: emerging works, future opportunities and a design framework. *arXiv preprint arXiv:2009.10228*.. https://doi.org/10.48550/arxiv.2009.10228