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An Evaluation of Artificial Intelligence Chatbots Ethical Use, Attitudes Towards Technology, Behavioral Factors and Student Learning Outcomes in Collegiate Aviation Programs

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Despite the potential opportunities of Generative Artificial Intelligence (AI) Chatbots in higher education, ethical concerns surrounding their use, such as biased data assumptions and plagiarism, have been raised. Despite studies examining these concerns in higher education, there seems to be a gap in evaluating perceptions of constructs: ethical use, attitudes towards technology, behavioral factors, and student learning outcomes relating to Generative AI Chatbots in Collegiate Aviation Programs in the U.S. Using perceptions of aviation students from six universities in the U.S. (n=271), a modified Technology Acceptance Model (TAM) of the constructs fit the empirical data well; most hypothesized relationships were significantly supported. The most substantial direct relationship was between attitude towards AI Chatbot use and behavioral intention to use AI Chatbots. Despite deep concerns about the ethical use of AI Chatbots in collegiate aviation programs, the model could explain about 59% of the variances in user behavior, suggesting relatively good user behavior among respondents. Graduate respondents had higher user behavior than first—and second-year undergraduates, who had higher scores on ethical use concerns. Male respondents showed higher user behavior than female respondents. By understanding students' perceptions, administrators can create well-informed policy guidelines and strategies for the responsible and effective integration of AI Chatbot tools in collegiate aviation programs pedagogy.

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Introduction

Artificial Intelligence (AI) has brought about a significant shift, revolutionizing the landscape of higher education (Zhai et al., 2021). This transformative technology has emerged as a catalyst, presenting thrilling prospects to elevate learning outcomes and educational efficiency within higher education (Xu & Ouyang, 2022; Yannier et al., 2020). AI, in its broadest sense, involves the development of computer systems capable of performing tasks that traditionally necessitate human intelligence, such as learning, reasoning, perception, and decision-making. It is a rapidly evolving field that encompasses a variety of techniques, including machine learning, deep learning, natural language processing, automatic speech recognition, computer vision, and robotics (Russell, 2010; Toumi, 2018).

Generative AI is a branch of AI that uses algorithms and models to create new and original content—such as text, images, video, audio, or software code—in response to a user's prompt or request (IBM, 2024). A Chatbot is a computer program designed to simulate conversation with human users, especially over the Internet, and a generative AI Chatbot is an open-domain chatbot program that generates original combinations of language rather than selecting from pre-defined responses (Adamopoulou & Moussiades, 2020; Codecademy.com., 2024). Generative AI Chatbots, like Open AI's Chat Generative Pre-Trained Transformer (ChatGPT), are not just theoretical concepts but practical tools actively used in higher education (McGrath et al., 2024; Open AI ChatGPT, n.d.). These Chatbots are trained using Reinforcement Learning from Human Feedback (RLHF), a process that involves training a model to make decisions and take action in an environment while receiving feedback from human experts through rewards, preferences, or demonstrations and helps guide the model's learning process (Jeyaraman et al., 2023; Open AI ChatGPT, n.d.).

Various iterations of Chat GPT have evolved, and they have the capability to assist with a wide range of tasks, such as providing personalized tutoring for students, reviewing resumes, helping researchers write grant applications, and assisting faculty with grading and feedback (OpenAI Platform, n.d.; Okonkwo & Ade-Ibijola, 2021). Gemini, formerly known as Bard, is another Generative AI Chatbot developed by Google that is natively multimodal. Gemini stands out with its unique ability to generalize and seamlessly understand, operate across, and combine different types of information, including text, code, audio, image, and video (Google Deep Mind, n.d.). Gemini is a Large Language Model (LLM) built on the more powerful Pathways Language Model (PaLM) 2 of the next-generation language model with improved multilingual, reasoning, and coding capabilities (Google Deep Mind, n.d.; Metz & Grant, 2024).

Windows Copilot, formerly Bing Chat, is another AI-powered virtual assistant developed by Microsoft and built on OpenAI's ChatGPT model. Window Copilot has features such as a conversational chat interface, image creation, and text generation that summarizes text and can write code in popular programming languages like JavaScript, C, and Python (Microsoft, n.d.). Claude is another Generative AI Chatbot developed by Anthropic that uses a different training method from GPT and Bard and aims to focus on safety and helpfulness (Anthropic, n.d.). Claude performs complex cognitive tasks beyond simple pattern recognition or text generation. Claude can transcribe and analyze almost any static image, generate codes, and provide multilingual processing (Anthropic, n.d.).

Within collegiate aviation programs, ground school academic courses and graduate-level aviation/aerospace research can benefit from the utility provided by AI-educational tools such as Generative AI Chatbots. Kasneci et al. (2023) suggest that these tools can enrich students' learning experiences, offering personalized support and potentially boosting academic performance With a high demand for extra-tutoring for large class sizes in some of the collegiate aviation programs in the U.S, these intelligent agents (Chatbots) can answer questions and replicate and process human communication, enabling individuals to interact with digital devices as if conversing with real people (Clarizia et al., 2018).

For professors and teaching assistants, Jafari and Keykha (2023) suggest that Generative AI Chatbots can enhance curricula design, teaching methods, and assessments in undergraduate and graduate collegiate aviation programs, leading to effective student learning outcomes (SLO). Other researchers like Cotton et al. (2023) suggest that Generative AI Chatbots can be used to assess various learning outcomes, such as knowledge, skills, and attitudes, as part of the ground school training course outline. In any academic pursuit, the ultimate goal for both professor and student is when both normative and objective assessments indicate a successful alignment of course objectives with student learning outcomes (SLOs). SLOs are statements that specify what students will know, be able to do, or be able to demonstrate when they have completed a course or program (UND, 2024). These outcomes are observable and measurable and demonstrate the knowledge, skills, attitudes, and habits of mind that students acquire from their learning experiences (Maki, 2011).

As part of any academic program of study, there should be evidence that individual students possess and demonstrate competencies required upon completing a learning experience or sequence of learning experiences (Eltabakh & Ahmed Ismail, 2019). Recent advances in flight deck technology, flight planning, and training tools may require collegiate aviation graduates to have AI-technological literacy and competencies (Pilon, 2023). AI tools leverage advanced algorithms and machine learning to process vast data and provide highly accurate route suggestions while accounting for real-time weather updates, air traffic congestion, and other crucial factors (Pilon, 2023). Introduction to AI tools at the collegiate levels and knowledge about Generative AI Chatbots can be helpful in better equipping aviation students with desirable technological competencies.

Despite the promising opportunities of Generative AI Chatbots in collegiate aviation programs, it is crucial to address the ethical use (EU) concerns surrounding them (Jeyaraman, 2023; Parson, 2021) and assess the levels of use among various demography of students. The ethical use of artificial intelligence involves optimizing its beneficial impact while reducing risks and adverse outcomes (IBM, n.d.). Hauer (2022) suggests that AI technologies should be developed, deployed, and used with an ethical purpose based on respect for fundamental rights and societal values. Ethical use concerns such as the need for informed consent, privacy breaches, biased data assumptions, fairness, and accountability are significant with the rapid use of AI educational tools in higher education (Sacharidis et al., 2020). User confidentiality and integrity (Zawacki-Richter et al., 2019) are also at stake. These EU concerns have also been suggested to impact attitudes and intentions to use AI-educational tools in higher education settings (Cotton et al., 2023; Dehouche, 2021; Kumar et al., 2024).

Literature Review

AI Chatbots and Collegiate Education

In a study on the effect of AI Chatbot-assisted learning on various components and how different moderator variables influenced its effectiveness, Deng and Yu (2023a) used a meta-analysis that reviewed 32 empirical studies with 2201 participants published between 2010 and 2022. The findings suggested that AI Chatbots could significantly improve explicit reasoning, learning achievement, knowledge retention, and learning interest despite negative findings in critical thinking, learning engagement, and motivation.

Labadze, Grigolia, and Machaidze (2023) found that students primarily gain from AI-powered Chatbots in three key areas: homework and study assistance, a personalized learning experience, and developing various skills. For educators, the main advantages are the time-saving assistance and improved pedagogy. However, the researchers also emphasize significant challenges and critical factors that educators must handle diligently. These include concerns about AI applications, such as reliability, accuracy, and ethical considerations.

Metcalfe (2017) suggests that timely formative feedback from a professor or instructor to students can help students learn. However, providing frequent quality feedback requires much time and effort from professors, and an AI Chatbot might help give students frequent, immediate, and adaptive feedback for academic tasks assigned to students. Tutoring is an essential part of effective pedagogy. It focuses on skill-building in small groups or one-on-one settings and can benefit learning (Robinson et al., 2021).

Effective tutors normally use questioning techniques, collaborative problem-solving, and personalized instruction to support their students (Robinson et al., 2021). Accessibility to a wider range of tutoring services in some universities that meet students' unique needs can also be a challenge, and this is where AI Chatbots can supplement tutoring services (OpenAI Platform., n.d.). In some collegiate aviation programs, one-on-one tutoring with a professor can present practical challenges necessitated by time constraints and the number of students in the class; hence, using such AI Chatbots can be beneficial to generate explanations and analogies for concepts in aviation or asking open-ended questions that stimulate further thinking (OpenAI Platform, n.d.).

Metacognitive skills can help students understand how learning works, increase awareness of gaps in their learning, and lead them to develop study techniques (Santascoy, 2021). Collegiate aviation students could use AI Chatbots to reflect on their experience working on a group project or to reflect on how to improve their study habits. A well-functioning team can leverage individual team members' skills, provide social support, and allow for different perspectives. This can improve performance and enhance the learning experience (Hackman, 2011). For example, in academic courses in aviation emphasizing team and scenario-based learning, such as Crew Resource Management, team members assigned can use an AI Chatbot to synthesize ideas, develop a timeline of action items, or provide differing perspectives or critiques of the team's ideas as suggested by Rahman and Watanobe (2023).

The process of organizing knowledge, teaching it to someone, and responding to that person reinforces one's own learning on that topic (Carey, 2015, p. 102). Carey (2015) further suggests that students can simulate or role-play how novice learners adapt to course materials by prompting AI Chat GPT for inputs on topics related to a course. This is also important in a student's ability to transfer skills and knowledge learned to a new situation, which usually involves abstract thinking, problem-solving, and self-awareness (Deng & Yu, 2023b).

Al-Zahrani (2023), in a study on the impact of generative AI Chatbots on researchers and research in higher education, suggested positive attitudes and a high level of awareness regarding these Chatbots in research. Respondents recognize the potential of these tools to revolutionize academic research and highly beneficial experiences using Generative AI Chatbots to expand project scope and improve efficiency. Positive attitudes toward Generative AI Chatbots in education have been suggested by Adeshola and Adepoju (2023).

Limitations and Challenges of AI Chatbot Use

Some challenges of using AI Chatbots in higher education need to be highlighted. AI Chatbots, primed from Large Language Models (LLMs), can produce incorrect yet plausible information confidently presented as factual. Mollick and Mollick (2023) suggest that this kind of hallucination or confabulation stems from how these systems work and the limits of their training data. AI Chatbots tend to make mistakes when prompted to provide quotes, citations, and specific detailed information. Different LLMs vary; most have become more sophisticated and less prone to making errors over time. Mollick and Mollick (2023) strongly suggest that users always fact-check the output of AI Chatbots with reliable external sources when using them to get information.

Developers train AI Chatbots on vast but still limited digital data sets, which can produce content that perpetuates harmful biases and stereotypes. Most training data comes from Western perspectives in the English language and is available online. With their inherent biases, human engineers also provide additional training for these tools. Individual users discuss their perspectives with a chatbot through prompts and queries. All these can result in subtle biases and stereotypes in the output of a chatbot. (OpenAI Platform, n.d.).

Like any technology, access to these tools may vary among categories of collegiate aviation students, and lack of access can perpetuate existing inequities. Concerns have been raised about the cost of subscriptions, access to computers and reliable connectivity, geographic restrictions, accessibility issues for people with disabilities, the user's preparation, and the tools' performance in other languages (Chan & Hu, 2023; Jafari & Keykha, 2023).

Ethical Use (EU) Issues with AI Chatbot Use in Collegiate Aviation Programs

One of the significant ethical use issues with AI Chatbots in higher education and research is the possibility of plagiarism (Loh, 2024). AI essay-writing systems are designed to generate essays based on parameters or prompts. This means that students could use these systems to cheat on their assignments by submitting essays that are not their own (Dehouche, 2021; Kumar et al., 2024). Fairness for class productive work is another assessment-related concern that impinges on learning outcomes, as Eke (2023) and Farazouli et al. (2023) suggested. Some students using

Chatbots can generate high-quality written assignments and have an unfair advantage over other students who do not have access to the tool, leading to inequities in the assessment process (Cotton et al., 2023). Other concerns are difficulty in adequately assessing a student's understanding of class materials when the student uses Chatbots to answer examination questions (Eke, 2023).

Other ethical concerns relate to privacy, bias, and transparency. Currently, privacy laws and regulations concerning AI Chatbots remain evolving and unclear in the U.S., and there is a likelihood that developers of AI Chatbots may use end-user data according to their terms of service (Parson, 2021; Williamson et al., 2020). That raises serious risk concerns about sensitive or private data inadvertently entered into an AI Chatbot by students (Popenici & Kerr, 2017; Hutson et al., 2022). Some studies have also highlighted the ethical risks associated with using AI in education, such as the risk of perpetuating biases and discriminating against marginalized groups (Yadav & Heath, 2022). Other studies have emphasized the necessity of ethical frameworks to guide AI implementation in education (Dwivedi et al., 2023). Breines and Gallagher (2020), in discussions on teacher bots, suggest AI is deceptive, implying that it intentionally undermines and competes with human agency.

As part of the phenomenon of “datafication” of higher education, which can be a by-product of Generative AI Chatbot use, Williamson et al. (2020, pg. 352) contend that “AI products and platforms can learn from experience to optimize their own functioning and become self-adaptive and further caution against trusting the ‘magic’ of digital quantification, algorithmic calculation, and machine learning.” Interestingly, Kwet (2019) cautions against the datafication of higher education by associating it with technocratic control, data harvesting, and exploitation in controlling the digital ecosystem. Kwet (2019) further argues that big technological corporations control computer-mediated experiences, giving them direct power over political, economic, and cultural domains of life, and such datafication introduces vulnerabilities to the educational system.

The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) conceptualized by Davis (1989) provides a framework to understand and evaluate how people accept and use technology. The initial TAM is based on the Theory of Reasoned Action (TRA), developed by Fishbein and Ajzen (1975), which predicts the attitudinal underpinnings of behaviors across a wide range of areas. TAM elucidates the technology determinant acceptance, which can explain the behavior while simultaneously justifying the theoretical and economic viewpoints (Davis, 1989). The TAM has five constructs, namely: perceived ease of use (PEU), perceived usefulness (PU), attitude towards use (ATU), behavioral intention (BI), and User Behavior (UB). These constructs are considered the primary determinants for users concerning application and technology acceptance (Ma & Lui, 2005; Venkatesh et al., 2003).

According to Davis (1989), ATU is an individual’s negative or positive viewpoint toward conducting the intended behavior in applying a given system. The construct BI is the level at which particular technology users have shaped a plan of intent to continue utilizing or not a particular technology with their future behavior. UB is the degree of usage application of a specific technology in terms of frequency (how often) and the measured volume (how much) when using a given technology by users. TAM has been used to assess perceptions of technology in video gaming and family-life dynamics (Bassiouni, 2019), consumer perceptions of usefulness and attitude toward e-shopping and its adoption (Ha, 2009), internet banking (Yousafzai, 2010), online travel reviews and user-generated-content (UGC) adoption (Assaker, 2020), mobile phone technology, automated road transport (Madigan et al., 2017) and healthcare/medicine (Yetisen et al., 2018).

Some studies have used various underlying constructs of TAM to examine user behavior when teaching online and using Learning Management systems in higher educational settings (Wingo et al., 2017; Luo et al., 2021). Chumo & Kessio (2015) used a variant of TAM to assess Information Communication Technology (ICT) use among tertiary students in Kenyan Public Universities and found that the model explained 78.24% of the variance of the student's behavioral intention to use web-based information systems. A similar study was conducted by Aliaño et al. (2019) using a variant of TAM to examine the factors that determine the use of mobile learning in higher education contexts. The findings suggested a high predisposition for using mobile devices for learning, with a direct positive effect regarding the relationships between the TAM constructs.

Research Objectives

A comprehensive understanding of how ethical perceptions of AI Chatbots influence attitudes towards AI Chatbots, their impact on intentions to use, and ultimately perceived learning outcomes is essential for formulating policies and guidelines in higher education, specifically collegiate aviation programs. Despite all the studies that highlighted the effect of ethical use on AI chatbot useability in higher education, there seems to be a paucity of research that assesses the inter-relationships between ethical concerns of AI Chatbot use, user attitudes, behavioral intentions, user behavior, and student learning outcomes in collegiate aviation education.

Adopting constructs from the TAM, we examine the impact of ethical use (EU) concerns on ATU, BI, UB, and SLO and hypothesize relationships among these variables. Understanding collegiate aviation education respondents' perceptions of the strength of relationships between these factors can be instructive in formulating policies, processes, and procedures for effective teaching, learning, and research when using these tools.

Research Questions

In line with the research objectives, we posed the following research questions that will guide us to understand the research problem:

1. What are the strengths of relationships between AI Chatbot ethical concerns for use, attitudes towards use, behavioral intentions, user behavior, and student learning outcomes?
2. What are the differences in EU, ATU, BI, UB, and SLO perceptions among demographic variables, age, gender, majors, and academic levels?

Based on the TAM and supporting the research questions, we hypothesized the following relationships, which were explored in the study:

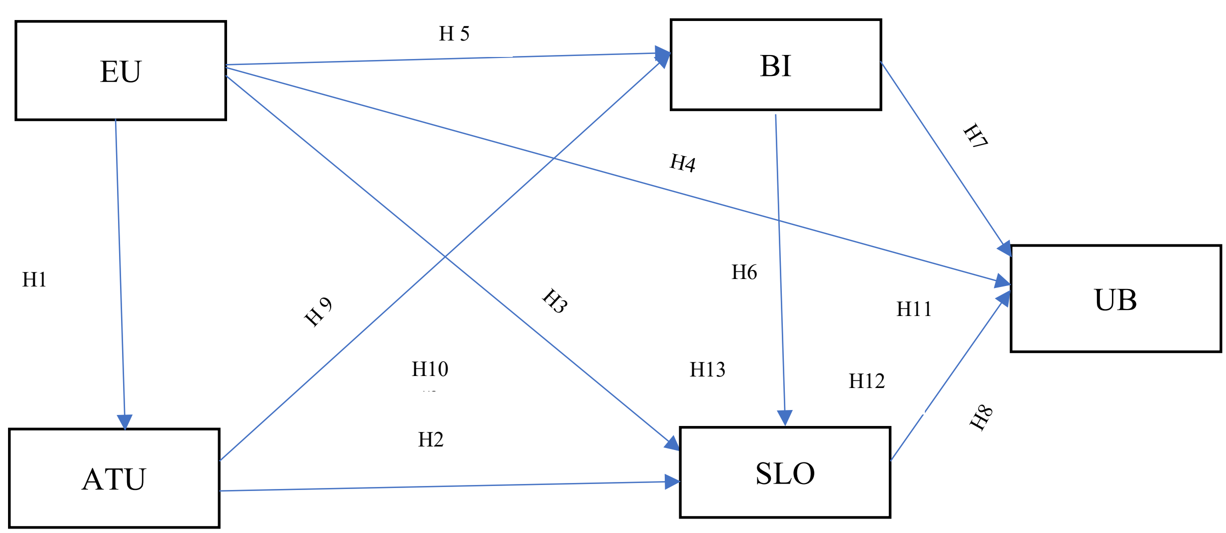
1. H1: EU has a direct relationship with ATU.

2. H2: ATU has a direct relationship with SLO.
3. H3: EU has a direct relationship with SLO.
4. H4: EU has a direct relationship with UB.
5. H5: EU has a direct relationship with BI.
6. H6: BI has a direct relationship with SLO.
7. H7: BI has a direct relationship with UB.
8. H8: UB has a direct relationship with SLO.
9. H9: ATU has a direct relationship with BI
10. H10: EU has an indirect relationship with SLO.
11. H11: EU has an indirect relationship with UB through SLO.
12. H12: BI has an indirect relationship with UB through SLO.
13. H13: ATU has an indirect relationship with SLO through BI.

We further provided a graphical representation of the hypothesized pathway for the relationships among the study constructs. Figure 1 shows these paths of relationships.

Figure 1

Path model showing the hypothesized relationships between constructs



Methods and Materials

We created an online and anonymous survey instrument to elicit respondents' perceptions of the strength of relationships between the study constructs. The survey items for the TAM constructs (ATU and BI) were derived from Venkatesh et al. (2003) and Lin and Yu (2023) and formed part of a broader research on AI Chatbot use in collegiate aviation. The items for ethical use (EU) were derived from Nguyen et al. (2023). The items for the student learning outcomes (SLO) were obtained from the Students' Evaluation of Learning and Instructions (SELFI), which is a validated instrument used by the University of North Dakota (UND) for evaluating students' learning outcomes (UND, 2024). The survey instrument was in English with a seven-point Likert-style scale (1= strongly disagree to 7 = strongly agree). The open-ended items elicited types of AI

Chatbots used by respondents and general opinions on AI Chatbot use in collegiate aviation programs. Table 1 provides examples of scale items.

Table 1
Study Construct Scale Item Examples and Sources

Study Construct (TAM)	Example of Scale Item	Source
Attitude Towards Technology Use (ATU)	I have a generally favorable attitude toward using AI Chat GPT.	(Venkatesh et al., 2003; Lin & Yu, 2023)
Behavioral Intention (BI)	I intend to use AI ChatGPT for my scholarly work frequently.	(Venkatesh et al., 2003; Lin & Yu , 2023)
User Behavior (UB)	I always prepare well for classes because of regular AI Chatbots use.	(UND, 2024; Venkatesh et al., 2003; Lin & Yu, 2023)
Student Learning Outcome (SLO)	AI Chat GPT use helps me develop in-depth knowledge of various aviation topics.	UND (2024)
Ethical Use (EU)	The use of AI ChatGPT can lead to cheating and plagiarism in scholarly works.	Nguyen et al. (2023)

Note: The entire survey is attached in Appendix A.

Sampling and Survey Administration

The study sample was purposefully drawn from a cross-section of undergraduate and graduate student populations enrolled in U.S. collegiate aviation programs with membership in the University Aviation Association (UAA). A University of North Dakota (UND) institutional review board (IRB) approved the protocols for the study. An anonymous online survey instrument was created via a Qualtrics® UND institutional account. Even though there are 2-year collegiate aviation programs in the U.S., we limited the scope of our sample by focusing on distributing the survey instrument to four-year degree-awarding collegiate aviation programs.

The anonymous survey link was sent to the respondents with the assistance of aviation program chairs at twelve UAA member institutions in the U.S., who facilitated the dissemination of the link via students' institutional emails and departmental listservs. The surveys also had QR barcodes that could be shared via phones and social media to enable easy sharing among the targeted respondents. The survey was also advertised through posters with scannable QR codes on various students' notice boards and electronic boards at various campuses. The survey link and QR codes were also sent to aviation student organizations at the various campuses for posting on their social media handles. For example, at UND, the digital poster was sent to the Students Aviation Advisory Council (SAAC) to be posted on various social media handles such as Facebook®, Twitter now X®, and Instagram®. The dissemination and collection period was from 20th January 2024 to 20th March 2024.

Results

Preliminary Data Collection and Analysis

At the end of the dissemination and collection period, two hundred and seventy-one (n=271) responses were obtained via the Qualtrics® data collection and analysis tool. About seven respondents did not disclose any demographic details. The quantitative data was downloaded from the Qualtrics site using an SPSS sav—file format for further analysis. The textual responses were analyzed using a Qualtrics tool and will be highlighted in detail. The details of the demographic variables are outlined in Tables 2 and 3.

Table 2
Academic Levels and Age of Respondents

Academic Level	n	Percentage
Undergraduate (1st & 2nd) Years	86	31.7
Undergraduate (3rd & 4th) Years	114	42.1
Graduate (Masters & Doctoral)	64	23.6
Undisclosed	7	2.6
Total	271	100
Age		
18-22	161	59.4
23-27	72	26.6
28-32	31	11.4
Undisclosed	7	2.6
Total	271	100

Table 3
Gender, Academic Majors, Chatbot Use Frequency

Gender	n	Percentages
Male	162	59.8
Female	102	37.6
Undisclosed	7	2.6
Total	271	100
Academic Majors		
Professional Flight/Commercial Aviation	161	59.3
Air Traffic Management	4	1.5
Aviation Technology	1	0.4
Uncrewed Aerial System (UAS)	17	6.3
Airport Management	20	7.4
Others	60	22.5
Undisclosed	8	2.6
Total	271	100
Chatbot Use Frequency in the Semester		
Never	93	34.4
Sometimes	118	43.5
About half of the time	15	5.5
Most of the time	1	0.4
Undisclosed	44	16.2
	271	100

Under the academic majors of Table 3, the "others" were primarily graduate students and some undergraduates with double majors. Some of the academic majors provided in the write-in space provided for other were aerospace sciences, atmospheric sciences, aviation safety and operations, computer science, aviation technician and maintenance, geography, and aviation public policy. Respondents were also asked to provide information on which AI Chatbots they usually use and any other comments.

Qualitative Analysis

We used a deductive approach for the open-ended responses provided by respondents since we had already outlined our research questions and keywords to align responses to specific questions. Qualtrics® Text iQ is a powerful text analytics tool integrated into the Qualtrics platform. It helps analyze open-text responses from surveys and uncover valuable insights. Text iQ can determine the sentiment (positive, negative, neutral) of the text, helping a researcher to understand the overall mood of respondents (Qualtrics, n.d). We used the Text iQ tool to identify and categorize common themes and topics within the 79 textual responses received (n =79). The tool allowed us to see what topics and words were frequently mentioned.

The utility of this TextiQ was that it automatically tagged and organized text responses, which helped align keywords/codes with specific textual responses. Using a dashboard, we visualize the analyzed data. One of the authors did the initial qualitative analysis of textual responses and produced the dashboard with keywords aligned with responses to form topics. The author's output was cross-verified by the other two authors, who independently reviewed the keywords, topics, and counts on the dashboard and their corresponding textual responses to ensure accuracy. We focused on using these qualitative responses to provide context during the discussion of the findings.

We assigned percentage frequencies based on each chatbot type's total number of mentions of all Chatbots identified. The output of the coding suggests that about 82% used Open AI's Chat GPT, 8% used BARD AI now Gemini, 4% used Quillbot, 2% used Snapchat AI, and 1% each for Claude, Grammarly, Bing AI, and Perplexity AI. Respondents were also asked to provide their institutions as an optional request. The qualitative results were collated and showed responses from participants enrolled in collegiate aviation programs at the University of North Dakota, Embry-Riddle Aeronautical University – Daytona, Purdue University, Dubuque University, Middle Tennessee State University, and Eastern Kentucky University.

Quantitative Analysis

Normality of Data and Descriptive Statistics

The IBM SPSS® Version 28 was used for descriptive and inferential computations as part of the preliminary analysis. The data was checked for normality to ensure that assumptions of linearity were not violated, and a visual inspection of Histograms for all the constructs was done. There were no indications of any abnormality, as evidenced by the skewness (.138 - 1.0) and kurtosis (-.035 – 1.8) values of the constructs being less than 3.000, which Kline (2016) recommends as a threshold for data to be considered normal.

Confirmatory Factors Analysis, Model Fit, Reliability Analysis, and Convergent Validity

We used Confirmatory Factors Analysis (CFA) to assess the fit of empirical data to the hypothesized model and the dimensionality of the various constructs. We used the IBM AMOS® version 26 for all model assessments. The chi-squared ($\chi 2$) index, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker-Lewis Index (TLI), incremental fit index (IFI), and the normed fit index (NFI) were used to assess model fit. According to Hu and Bentler (1999), implementing TLI and CFI cutoff values of 0.95 in conjunction with an RMSEA cutoff value close to 0.06 appears to result in lower Type II error rates at the cost of Type I error acceptable rates. An RMSEA of less than 0.05 is desirable, whereas values greater than 0.10 suggest problems with the model's fitness (Kline, 2016). The normed fit index (NFI) and the incremental fit index (IFI). NFI and IFI values should be greater than 0.90; otherwise, it indicates the need for model enhancements (Bentler & Bonett, 1980).

Due to low loading, we had to remove some items in various constructs to improve the model fit. The items removed were ATU_4, UB_3, EU_5, and EU_6. The removal was based on recommendations from the modification indices of AMOS and theoretical guidance for the parsimony of items underlying each construct. A final CFA structural model was obtained, which provided moderately acceptable fit indices [$\chi2 = 223.649$, $p < .001$, PCMIN/DF = 1.804, NFI=.927, RFI =.901, IFI =.966, TLI = .953, CFI = .966, RMSEA =. 055 (.043 - .066)] for all the constructs.

The average variances extracted (AVE) approach was used to determine convergent validity, which refers to how closely a new scale is related to other variables and measures of the same construct. Fornell and Larcker (1981) recommend a value greater than 0.50. The AVE for all constructs was greater than the 0.50 threshold, suggesting acceptable convergent validity. Field (2018) and Hair et al. (2010) recommend a value of .70 or greater in determining survey item acceptability, reliability, or consistency. All the items had values greater than the .70 threshold. Table 4 shows the descriptive statistics of the study variables, the Cronbach's alpha, composite reliability, and AVE values.

Table 4

Descriptive Statistics of the Study Variables, Reliability Test, and Convergent Validity Test

	Number of Items	Mean		Cronbach's Alpha	Composite Reliability	Average Variance Extracted
					CR	AVE
Construct	Statistic	Statistic	Std. Error	Statistic		
ATU	3	4.10	.010	.92	.92	.79
BI	3	3.52	.069	.91	.90	.75
EU	4	5.28	.092	.82	.81	.54
SLO	4	3.80	.102	.91	.91	.71
UB	4	3.70	.148	.87	.85	.60

Note: All the α-vales for reliability were above the .70 threshold recommended. All constructs had AVE values ≥ .50 threshold recommended by Fornell and Larcker (1981) for evidence of convergent validity.

Discriminant Validity

The instrument's discriminant validity was found acceptable by comparing the square root of the AVE for constructs to the correlation coefficients for each variable. The square roots of the AVE on the diagonal line were greater than all other correlations in the corresponding columns and rows, as shown in Table 5. The results indicated that the covariates could be significantly distinguished from one another.

Table 5
Results of the Discriminant Validity Test

	ATU	EU	BI	SLO	UB
ATU	**.89**				
EU	-.529**	**.73**			
BI	.740**	-.347**	**.89**		
SLO	.731**	-.438**	.717**	**.84**	
UB	.715**	-.565**	.643**	.707**	**.77**

Note: Square roots of AVE are in bold on the diagonal. **. Correlation is significant at the 0.01 level (2-tailed).

After the preliminary data analysis, we assessed the strengths of relationships between AI chatbot ethical concerns for use, attitudes towards use, behavioral intentions, user behavior, and student learning outcomes. We also determine differences in the mean of respondents' perceptions of the study variables EU, ATU, BI, UB, and SLO based on demographic variables, age, gender, majors, and academic levels.

Research Question One

To answer the first research question, "*What are the strengths of relationships between AI chatbot ethical concerns for use, attitudes towards use, behavioral intentions, user behavior, and student learning outcomes?*" a hypothesized model was assessed using goodness-of-fit indices and squared multiple correlations derived from maximum-likelihood estimations. The IBM SPSS® AMOS 28 Graphics was used for all the structural equation model (SEM) path analysis, and bootstrapping was used (2000 bootstrap samples). Bootstrapping is a non-parametric method based on resampling with replacement, which is done many times, e.g., 2000 times (Bollen & Stine, 1990; Shrout & Bolger, 2002).

An initial measurement model with all the paths as proposed did not yield good fit indices [$\chi 2$ = 13.842, p = .000, PCMIN/DF = 13.842, NFI=.983, RFI =.833, IFI =.984, TLI = .843, CFI = .984, RMSEA =. 218 (.126 - .326)]. The path between EU and BI was not significant, and the modification indices recommended for that path to be removed to improve the model. Removing that path improved the measurement model, resulting in good fit indices [$\chi 2$ = 1.546, p = .214, PCMIN/DF = 1.546, NFI=.998, RFI =.981, IFI =.999, TLI = .993, CFI = .999, RMSEA =. 045 (.000 - .176)] was obtained. Table 6 shows the critical ratios, regression weights, p-value, squared multiple correlations, and hypothesis statements of the model with good fit indices.

Table 6
Table showing Maximum Likelihood Estimates, Standard Error, Critical Ratio, P-values, Regression Weight, and Hypothesis Statements

Path	**Estimate**	**S.E.**	**C.R.**	***P***	**β**	**Hypotheses**
ATU<---EU	-.757	.074	-10.207	***	-.528	Supported
BI<---ATU	.758	.042	18.053	***	.740	Supported
SLO<---ATU	.355	.056	6.282	***	.384	Supported
SLO<---BI	.358	.051	7.044	***	.398	Supported
SLO<---EU	-.128	.059	-2.166	.030	-.097	Supported
BI<---EU	-	-	-	-	-	Path removed.
UB<---BI	.432	.073	5.915	***	.484	Supported
UB<---EU	-.323	.057	-5.634	***	-.246	Supported
UB<---SLO	.306	.058	5.228	***	.308	Supported

Note: p-value *** is at the p < .001 level (2-tail).

The measurement model had significant explanatory powers measured by the squared multiple correlations (SMC) values of the endogenous variables (ATU, BI, UB, and SLO). The hypothesized model suggests that EU explained about 27.8 % variance of ATU. ATU explained about 54.7% of BI. EU, ATU, and BI explained 61 % of SLO. BI and SLO explained about 58.5% of UB. For the exogenous variable EU, the path coefficients provided a measure of the effect sizes (Kline, 2016), and the path with the largest effect size was ATU to BI. The path with the lowest effect size was EU to SLO. Table 7 shows the SMC values.

Table 7
Squared Multiple Correlations (R^2)

Construct	**SMC (R^2)**
ATU	.278
BI	.547
SLO	.610
UB	.585

Mediation Analyses

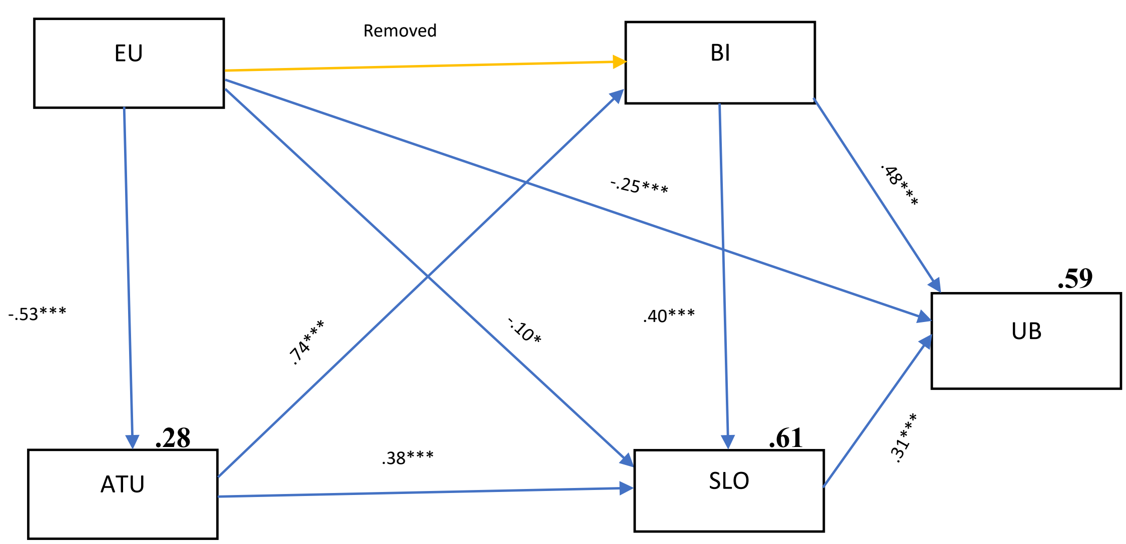
The check for mediation and the indirect effect was computed from these samples using the Hayes PROCESS® Version 4, which is an add-on to IBM SPSS Statistics® version 28, and a sampling distribution was empirically generated. According to Hayes (2022), a confidence interval is typically computed and checked to determine if zero is in the interval. If zero is not in the interval, then the researcher can be confident that the indirect effect differs from zero and that there is a mediation effect. Table 8 shows the mediation analysis outputs, and Figure 2 shows the hypothesized paths and mediation for the measurement model.

Table 8
Mediation Analysis

Pathways	*F (2,260)*	R^2	*P*	Stand. Indirect Effect	SE	95% Boot. CI LLCI - ULCI	Medn.	Hyp.
UB<-SLO<-EU	179.446	.550	***	-.249	.040	-.329 - -.173	Yes	Supported
SLO<-ATU<-EU	151.179	.538	***	-.365	.037	-.440 - -.294	Yes	Supported
SLO<-BI<-ATU	196.913	.602	***	.288	.068	.174 - .433	Yes	Supported
UB<-SLO<-BI	151,044	.537	***	.362	.043	. 277 - .447	Yes	Supported

Note: p-value *** is at the p < .001 level (2-tail). Boot. CI is the 95% Bootstrapped Confidence Interval with a lower limit (LL) and upper limit (UL). Medn. – Mediation; Hyp. – Hypothesis.

Figure 2
The final path analysis model shows the hypothesized relationships between constructs



Note: *** P < .001; *p< .05. The path between EU and BI (ns) was removed to improve the model.

Research Question Two

To answer research question two, "*What are the differences in EU, ATU, BI, UB, and SLO perceptions among demographic variables, age, gender, majors, and academic levels?*" a one-way analysis of variance (ANOVA) was conducted to determine if significant differences existed in the perceptions of the constructs among demographic variables (academic level, gender, and age groups). The Bonferroni test for post hoc analysis with a 95% percentile bootstrap confidence interval (BCI) was used since there were no violations of the homogeneity of variances, and 5000 bootstrap samples were used.

User behavior

For user behavior, only academic level showed significance. The ANOVA model, F(2,260) = 3.064, *p* = .048, eta-squared value = .023, suggested significant differences in the mean score for UB among the academic levels. A post hoc test using Bonferroni showed that the differences were between graduates [M = 4.10, SE= .167, 95% BCI (3.77 -4.44] with higher scores than the first and second-year undergraduates [M = 3.52, SE = .141, 95% BCI (3.26 – 3.80)]. There were no significant differences in the mean scores for SLO, BI, EU, and ATU among the academic levels.

Age Group

Another ANOVA model, F(2,260) = 2.913, *p* = .050, eta-squared value = .022, suggested significant differences in the mean score for UB for the age groups. A post hoc test using Bonferroni showed that the differences were between 28-32 [M = 4.28, SE = .276, 95% BCI (3.69 - 4.82] with higher scores than the 18-22 [M = 3.59, SE = .144, 95% BCI (3.37 – 3.81)]. A final ANOVA model, F(2,260) = 3.600, *p* = .029, eta-squared value = .027, suggested significant differences in the mean score for EU for the age groups. A post hoc test using Bonferroni showed that the differences were between 18-22 [M = 5.41, SE= .089, 95% BCI (5.41 – 5.59] with higher scores than the 28-32 [M = 4.48, SE = .200, 95% BCI (4.47 – 5.30)].

Gender

An independent T-test of means showed that there were significant differences in the mean scores on BI [t (261) = 2.417, p = .016, SE = .195, 95% BCI (.124 - .890)] among male respondents [M = 3.72, SE = .140, 95% BCI (3.44 – 3.97)] and the female respondents [M = 3.21, SE = .141, 95% BCI (2.93 – 3.49)]. All the other constructs did not show significance.

Discussions

Strength of Relationships Among Study Variables

The results from this study show the significant relationships between the ethical use of AI Chatbots and attitudes towards use, behavioral intentions, user behavior, and student learning outcomes among the respondents. The instrument used to evaluate the relationships had good reliability and construct/discriminant validity. A CFA model showed that the multi-dimensional structure of constructs and the interrelationships were consistent with the empirical data as observed by the fit indices, which were all acceptable. The path analysis model suggested that the hypothesized relationships among the study constructs were all supported, except for EU to BI, which was removed. The model could explain about 61% of the variances observed in SLO due to the predictive effects of EU, ATU, and BI. The model explained that about 59 % of variances observed in UB were due to the predictive effects of BI and SLO.

The results suggest that the hypothesized model significantly explained the relationships between ethical use and the other constructs: attitude towards use, student learning outcome, and user behavior. We found that these findings corroborate previous studies by Aliaño et al. (2019), Chumo & Kessio (2015), and Luo et al. (2021), where variants of the TAM were able to explain relatively higher variances in the underlying constructs. We also observed that the findings validate the utility and resilience of TAM in various disciplines. Ethical concerns had the highest mean score for respondents' perceptions of items compared to the scores for behavioral intentions, user behavior, and student learning outcomes. The findings suggest that the ethical concerns related to AI Chatbot use among this collegiate aviation sample adversely affect their behavioral intentions to use these tools, reflected in their actual user behavior, which aligns with previous findings by Ko and Leem (2021).

Regarding predictive relationships using the path analysis, the most significant effect size between EU and ATU suggested that ethical concerns negatively impact respondents' attitudes toward AI Chatbot use. Based on responses from the textual comments, which provided context and previous findings from Eke (2023), Farazouli et al. (2023), and Loh (2024), we surmise that some respondents are concerned about ethical issues such as plagiarism, fairness, and data privacy, and their potential impact on the value of university education, invariably influences their attitude towards using these AI-Chatbots. Other concerns related to the accuracy and transparency of information provided by AI Chatbots were noted in some of the textual comments and, as suggested by Parson et al. (2021), may be antithetical to a profession where professionalism and integrity are desired due to its safety-criticality. We think that these concerns can adversely influence attitudes towards AI Chatbot Use. These were some comments provided by respondents in the open-ended item, which aligned with topics/codes related to adverse ethical concerns:

> "*AI Chatbots in collegiate aviation education can lead to complacency in learning and understanding that's already faced with advancements in avionics/flight control systems. AI use for study can possibly cause complacency in studying/learning/and actually understanding material. Tied into the use of autopilot causing complacency amongst pilots, this could lead to complete reliance on automation, in terms of training*."
>
> "*I think it's good to keep it prohibited for plagiarism, so people actually learn the topics. It's a great tool for boosting your learning if you use it properly and not plagiarizing.*"
>
> "*I do not feel like they would be wise to use in a major that focuses on developing one's own critical thinking and problem skills and could lead to a loss of ADM if used excessively*."

This finding is similar to that of Peres et al. (2023), who also found out that some higher education students expressed reservations about AI Chatbot accuracy, transparency, privacy, over-reliance on technology, and ethics and how it adversely impacts higher education. It is also in tandem with findings that sometimes it is challenging to assess the validity or identify falsehoods of information and suggestions proffered by AI Chatbots, thus necessitating human oversight (Lubowitz, 2023). Another statement that aligns with a code related to trustworthiness from a respondent highlights this point:

> "*AI Chatbots" are incredibly prone to spitting out garbage information, there is no true search function or way to properly curate the answers it provides. They have no place in higher education, espeacially in a field as complex and dangerous as commercial aviation*."

> "*it is a helpful tool but should not be considered to be trusted 100% you should look over what they provide*."

The findings suggest that even though the EU had a very weak predictive relationship with SLO, the mediatory effect of ATU was evident. Respondents' concerns about the ethical use of AI Chatbots adversely impacted their attitudes to using AI Chatbots, which influenced their perceptions of AI Chatbots on student learning outcomes, supporting findings by Nguyen et al. (2023).

The significant direct relationship between ATU, BI, and SLO agrees with previous findings by Habibi et al. (2023), who also found that attitudinal and behavioral perceptions of AI Chatbots significantly influence student learning approaches and outcomes among higher education students and must also be framed within the context of policies such as mandatory use, easy access and derived benefits of use. We proffer a potential reason for this finding in the collegiate aviation environment, especially within the undergraduate programs. Some respondents may be concerned about potential certificate revocations and other disciplinary actions for using AI Chatbots in ground school courses governed by stringent CFR Part 141 Training Course Outlines (TCO) with detailed student learning outcomes.

This is because TCOs demand strict compliance with testing standards, and eliciting solutions or suggestions from AI Chatbots other than those of FAA-approved test standards may be risky as these answers may not be accurate per the test standards. Most undergraduate flight-related courses have minimal essay-type assessments for the FAA ground school test, focusing on technical areas such as regulations, weather, airmanship, risk assessment, human factors, flight physiology, and aerodynamics before practical flight tests.

Since most of the assessments are in the multiple-choice format, which requires accurate answers, most collegiate aviation students rely on FAA-approved text for guidance and may not elicit answers or cues from AI Chatbots, which may be perceived as not transparent and sometimes unreliable; however, in courses where some elements of writing and research are required such as crew resource management (CRM), aviation safety management, aviation business, and economics, there may be opportunities to use these AI Chatbots. That can account for a proportion of undergraduate student respondents who indicated using AI Chatbots.

Regarding ethical use concerns and student learning outcomes, we suggest that some respondents' concern about plagiarism becomes paramount as they face difficulty determining the originality of work generated by AI Chatbots, which is corroborated by the findings of both Cotton et al. (2023) and Farazouli et al. (2023). This can adversely affect their perceptions of the value of AI Chatbots in students' learning outcomes. It is also possible that inconsistent policies on AI Chatbots in some of the collegiate aviation programs and the constant admonishment from some professors on plagiarism risk for using AI Chatbots in written assessments can influence some of the respondents to develop a natural aversion to its use, which can impact their perceptions on AI Chatbots risk-benefit to their learning outcomes.

Student learning outcomes also significantly mediated the relationships between EU and UB, suggesting that the policies guiding students' learning outcomes development and expectations invariably influence how respondents use AI Chatbots based on their ethical use perceptions. A scenario where SLO in syllabuses and course outlines expects respondents to demonstrate knowledge and use of AI tools such as Chatbots at the end of a course can positively impact respondents' use of AI Chatbots since they are intrinsically tied to expected outcomes.

The results also showed that the relationship between ATU and SLO is further explained by the behavioral intentions to use (BI). It suggests that when respondents develop either positive or negative attitudes towards AI chatbot use, their intentions to use the technology are framed with the expectation that it will impact the SLO. Interestingly, despite all these ethical use concerns, the variances explained by the model for user behavior were almost 59%, which is quite substantial and suggests that most respondents used these AI Chatbots in one way or another for academic work. Some comments from respondents that align with the user behavior code highlighted these conflicting phenomena:

> *"I have a negative view of AI, but it has helped me with questions that I thought were too specific for Google."*
>
> "*I feel as though AI in general has a long way to go until it can be used reliably in a professional or academic capacity. This, combined with a negative outlook on AI has caused me to be apprehensive about using it. AI should be used as a tool in academics to provide ideas or to reduce the busy work that people must do in their education, allowing them to develop better critical-thinking skills and more in-depth ideas. Overall, the way that AI works does require people to continue to use it for it to develop, however, that further adds to the unpredictability that comes with AI.*"
>
> "*I like using AI not for factual overview of topics but as a quick reference on something I'm not familiar with as well as organization. I condemn the use for cheating in academics or writing papers. For me, it is a tool and not a solution*."

These findings agree with those of Chan and Hu (2023), who studied higher education students in Hong Kong, and Al-Zahrani (2023), who studied higher education students in Saudi Arabia. These researchers found that despite the ethical concerns over AI chatbot use in higher education, respondents were generally willing to use AI Chatbots for their studies and future work.

They found that students perceive AI Chatbots as beneficial for providing personalized learning support as they expect learning resources tailored to their needs.

Stöhr et al. (2024), in a study of AI chatbot use among Swedish university students, also found that more than half of the students expressed positive attitudes towards using Chatbots in education. However, almost as many expressed ethical concerns about future use. This concurrence suggests that ethical use concerns and impacts on attitudes to using AI, behavioral intentions, user behaviors, and learning outcomes may be similar in higher educational settings despite discipline-specificity and institutional and cultural context. It is also interesting that Stöhr et al. (2024) found that over a third of students regularly use AI ChatGPT in education and that using other AI Chatbots seemed minimal. This finding is similar to this study's findings and suggests Chat GPT's popularity compared to other Chatbots among university students.

Demographic Analyses

The demographic analysis suggested that graduates use AI Chatbots more than the first and second-year undergraduate students. This finding was consistent with recent findings by Stöhr et al. (2024), which suggested that undergraduate students generally were more negative than graduate students regarding overall positive attitude and the efficacy of Chatbots in improving their learning effectiveness, language ability, and study grades. Further, these students had stronger reservations about the role of Chatbots in education. They mostly perceived using Chatbots to complete assignments as cheating, which should be prohibited and goes against the purpose of education—some of the textual comments from undergraduate respondents in this study aligned with those from Stöhr et al. (2024). These were quotes from some undergraduate respondents:

> "*AI Chatbots should never be allowed in any college class, degree field, or master program. The use of AI Chatbots is cheating and plagiarism. Any college or university must have strict academic rules when it comes to cheating and plagiarism. AI Chatbots should fall under that. Giving credit where credit is due is one of the foundations of academics. AI Chatbots makes that foundation crumble, as credit is nowhere to be found in the sea of mass data pulled. Overall, AI Chatbots should never be allowed in any field, especially aviation education.*"

> "*I fundamentally agree with professors choosing to limit/ban the use of AI Chatbots for work in their courses; I believe they are detrimental to a college education*."

This observation is unsurprising since graduate students in most collegiate aviation programs engage in more research and written assignments as part of coursework and require extensive searches for literature and citations. It sounds logical since graduate coursework requires copious amounts of literature reviews and research writing for thesis and dissertations. For these graduate students, it is important to have efficient research and analysis support. That is where generative AI tools such as Chatbots facilitate literature searching and summarizing readings and may generate hypotheses based on data analysis, enabling them to stay up-to-date with the latest research trends and build upon initial insights for their own work, as Berg (2023) suggested.

These graduate students also find utilities with these Chatbots for search and academic writing, as suggested by Chan and Hu (2023), who found out that most students want feedback on how to improve writing skills, create and generate diverse and unpredictable ideas, and receive prompts beyond grammar checking and brainstorming. Despite the concerns about plagiarism and the potential for AI Chatbots to provide inaccurate information, these graduate students may possess the skillsets to screen AI Chatbots' suggestions and outputs using corroborative source checking and bibliographical indexing. These were some comments provided by respondents in the open-ended item that align with a code on usefulness:

> "*AI in general is useful when trying to find different resources for say a research paper. But it's also hard to tell if the student is only using AI for answers. But overall I have had a positive experience when using AI.*"

> "A*I is only telling us things that we have already told it, but more effectively. It is an extremely useful research and planning tool*."

> "*I think that AI Chatbots are great for research purposes. For me it acts as a search engine to where I am able to ask it a question and it is able to find information for me. This helps when I am stuck on something and am not quite able to figure it out*."

The primal fear of plagiarism experienced in early undergraduate coursework can be further exacerbated by some professors who are averse to using AI Chatbots, which may dissuade some early undergraduates from using AI Chatbots. That may not be similar in some aviation graduate courses with mostly adult learners. It is rather interesting that the graduate students being apt to use AI Chatbots seems at variance with findings from Deng and Yu (2023a), who suggest that graduate students may have some academic experience during their undergraduate study that does not require much use of such AI tools and may stick to traditional research and scholarly search tools such as printed materials and find challenges with using some of these AI applications. There were varying opinions from some undergraduate respondents about professors and programs allowing the use of AI Chatbots:

> "*I wasn't even aware that there were professors who were allowing and encouraging AI Chatbots.*"

> "*It should be made clear to us on its use. If we can use it I prefer to all do in class with the professor as a form of review that way the professor can see if the information listed is 100% correct.*"

On the other hand, this was an opinion from a graduate student:

> "*The use of AI Chatbots helps students stay engaged in their coursework, enabling them to persevere when faced with academic challenges and fostering a broader range of thinking. Since AI is utilized in the real world, it makes sense to leverage it as a valuable resource in academics as well. In the real world, you are allowed to use your resources, and academia should prepare us for this*."

As stated earlier, the apprehension of using Chatbots for ground school examinations or coursework seems realistic when there is currently no policy guidance by the FAA, and some collegiate aviation programs also have minimal guidance for use. These fears may be linked with the potential for certificate action (revocation of ground school assessment results). Currently, FAA ground school examinations are mostly multiple-choice options with standardized answers. AI Chatbots are not allowed, which may not incentivize their use since it may not benefit these young undergraduates seeking an FAA flight certificate. Graduate students are mostly engaged in non-flight certification-related courses in collegiate programs and have the flexibility to use AI Chatbots for their research work.

Based on the previous findings among the graduates and early undergraduates, It seemed logical for the 28-32-year-olds to have significantly higher scores than the 18-22. It is plausible that most of the 28-32-year-olds fall into the graduate group in most collegiate aviation programs. Bearman et al. (2022) suggested that AI chatbot user experience affects user behavior. The more positive experiences derived from Generative AI Chatbot use the more its value proposition function and tendency to use. Some older students may have family and work commitments that require the efficient use of time and effective apportionment. They may find using AI Chatbots functionally useful to get scholarly work, such as written assignments, done expeditiously to be able to attend to these other commitments. This was a comment from a 28-32-year-old respondent:

"*It takes my workload from 20+ hours to around 5 and allows me better mental health.*"

There were significant differences between male and female respondents regarding behavioral intentions. That was not surprising, as previous studies show that when there are no policies on the use of technology, and there seem to be ethical concerns about its use, female respondents tend to be more conservative in their intention to use such technology compared to males (Bearman et al., 2022). This finding was also consistent with Stöhr et al. (2024) study on students' adoption and perceptions of ChatGPT and other AI Chatbots in higher education. They found out that female respondents were ostensibly more concerned about the impact of AI on education, considered the use of Chatbots as potentially contrary to the purpose of education, and viewed the use of Chatbots in assignments and exams as cheating that should be prohibited. On the other hand, male respondents had an overall more positive attitude towards Chatbots and perceived them to a greater extent as tools that can improve their learning. From the findings, we suggest that as collegiate aviation programs develop policies on AI Chatbots, the gender context must be considered to ensure equitable access and use.

Implications for Policy

By understanding students' perceptions of these constructs, collegiate aviation program leadership can develop policy guidelines for AI Chatbots to address needs and concerns while promoting effective learning outcomes. Developing holistic policy guidelines for using these AI Chatbots that outline the scope, underlying benefits, and limitations is essential. The policy should also provide procedural guidelines for syllabi and class use, especially at the primacy levels in collegiate aviation programs. These policy guidelines must be developed with input from students, faculty, and technology resource persons in the program to ensure that data security and privacy issues are considered. Different policies and procedures should target graduates and undergraduates since this study suggests different user behaviors.

Our findings, which align with previous literature on AI Chatbot use in higher education (Al-Zahrani, 2023; Robinson et al., 2021), suggest that AI Chatbots have the potential to revolutionize traditional pedagogy in collegiate aviation programs. AI Chatbots and other AI educational tools can offer structured support for diverse learning needs, enhance efficiency, and promote self-directed learning, as Labadze, Grigolia, and Machaidze (2023) suggested. The successful integration of AI Chatbots in collegiate aviation programs may depend on how professors are educated through workshops to understand the utility, benefits, and limitations of the various AI Chatbots in higher education and how they develop their syllabi and SLO with that in mind.

Students must be well-informed about the benefits and potential pitfalls of using AI Chatbots for academic work. Professors play a key role in this by encouraging critical thinking and the need to cross-check information suggested by Generative AI Chatbots with other sources. These professors and teaching staff should set clear guidelines for using AI Chatbots and other resources appropriately and communicate them to students in their syllabi and course information. This could include guidelines on when and how AI Chatbots can be used and the proper citation and attribution of AI chatbot-generated text, as suggested by Chan and Yu (2023) and Bearman et al. (2022).

As the U.S. aviation regulator, the FAA can provide informational resources and advisory circulars highlighting advances in Generative AI Chatbots, their applicability in an aviation training environment, and the scope and limitations of their use. Institutions should consider providing educational resources and workshops to familiarize students with Generative AI Chatbot technologies and their ethical and societal implications.

This would enable students to make informed decisions when using these technologies in their academic endeavors. As extant research by Parson (2021) and Williamson et al. (2020) suggests, robust data protection policies and practices should be in place within collegiate aviation programs to safeguard users' privacy and to allay some of the fears associated with using AI Chatbots. We hope that based on some of the findings of this study, collegiate aviation programs will re-frame their policy, curricula, and teaching approaches to better prepare students for a future aviation industry where Generative AI Chatbots and technologies may become pervasive, bringing with them potential benefits such as enhanced operational experiences and efficiency.

Limitations

The sample size was relatively small for all collegiate aviation programs in the U.S., which should be considered. Collegiate aviation programs consist of two-year and 4-year undergraduate programs, but we did not have responses from any two-year programs, though we sent out the survey through UAA. We relied on self-reported data, which may also introduce potential biases, as participants could have been influenced by social desirability or inaccurate recall of their experiences with AI Chatbots. The data also suggested that the predominant AI Chatbot used by most respondents was the Open AI Chat GPT, which must be considered when interpreting the findings. We also limited our sample to 4-year collegiate aviation programs, even though there are some 2-year collegiate aviation programs.

Furthermore, the study's cross-sectional design does not allow for examining changes in students' perceptions over time as their exposure to and experiences with AI Chatbots evolve. Lastly, since some collegiate programs may not have a formal use policy in academic settings, students may have limited exposure to it. We also sampled our respondents early in the spring semester with minimal academic coursework. That could impact responses from fresh undergraduate students who may still be orienting themselves to the program's intricacies.

Conclusion

In conclusion, the perceptions of a sample of collegiate aviation program respondents were evaluated to determine the relationships between ethical use concerns of AI Chatbots, attitudes towards use, behavioral intentions, students' learning outcomes, and user behaviors. Some constructs from the technology acceptance model (TAM) were used to assess the strengths of relationships among these constructs. An SEM/PA measurement model fit the empirical data well; most of the hypothesized relationships were significantly supported. The most substantial direct relationship was between attitude towards AI Chatbot use and behavioral intention to use AI Chatbots.

Despite deep concerns about the ethical use of AI Chatbots in collegiate aviation programs stemming from cheating, plagiarism, loss of professor jobs, and data privacy, about 59% of the variances in user behavior could be explained by a model suggesting relatively good user behavior among respondents. Graduate respondents had higher user behavior than first—and second-year undergraduates, with higher scores on ethical use concerns. The 28-32-year-olds had relatively higher user behavior than the 18-22-year-olds. Male respondents showed higher user behavior than female respondents.

The insights gleaned from our study have the potential to significantly influence policy development around the integration of AI Chatbot technologies into higher education. By understanding students' perceptions and addressing their concerns, policymakers can develop well-informed guidelines and strategies for the responsible and effective implementation of AI tools, thereby enhancing teaching and learning experiences in higher education.

Future Direction

There is a need for further research as AI Chatbot use expands in higher education. Expanding our study to include other AI educational technologies, understanding how AI Chatbot technology is used among professors and collegiate aviation administrators, and probing the impact of AI Chatbots on future flight training and the AI-mediated aviation industry are all promising avenues for future investigation.

Ethical Disclosure: AI tools used were Qualtrics® TextiQ for coding and Grammarly® for editing and checking grammar and style.

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Appendix A

Sample of Survey Items

ATU_1: I generally have a favorable point of view toward using AI Chatbots.
ATU_2: I think using AI Chatbots for academic work is a good idea.
ATU_3: I am interested in learning about any new information related to the use of AI Chatbots in academic work.
ATU_4: How do you feel about the effect of AI Chatbots use on academic work? (removed)
BI_1: I plan to use AI Chatbots for my academic work in the future.
BI_2: I aim to use AI Chatbots for my academic work frequently.
BI_3: I hope to adapt AI Chatbots for academic work and professional development.
SLO_1: AI Chatbots help me to think analytically in aviation courses.
SLO_2: AI Chatbots help me deal with unfamiliar problems in aviation courses.
SLO_3: AI Chatbots use help me develop in-depth knowledge of various aviation topics.

SLO_4: How have AI Chatbots developed your critical thinking skills about aviation topics?
UB_1: The regular use of AI Chatbots in scholarly activities promote my active participation in academic activities.
UB_2: I am encouraged to ask questions and share ideas in classes where the professors regularly allow AI Chatbots as an academic tool.
UB_3: I regularly attend classes where professors regularly allow the use of AI Chatbots in their courses. (removed).
UB_4: I prepare well for classes because of regular AI Chatbots use.
UB_5: I put effort into my studies because of the regular use of AI Chatbots.
EU_1: The use of AI Chatbots can lead to cheating and plagiarism in academic works.
EU_2: Over-reliance on AI Chatbots can lead to students not developing critical thinking skills.
EU_3: The use of AI Chatbots can lead to a loss of human interaction and emotional connection among students.
EU_4: Accessibility to AI chatbot data should be transparent with informed consent and clarity of data ownership.
EU_5: AI Chatbots must ensure well-informed consent from the user and maintain the confidentiality of the user's information, both when they provide information and when the system collects information about them. (removed).
EU_6: AI Chatbots could lead to the loss of jobs for people working in academia and research fields. (removed).