Smart Learning Environments

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The influence of sociodemographic factors on students' attitudes toward AI-generated video content creation

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Abstract

Artificial Intelligence (AI) and Machine Learning (ML) technologies offer the potential to support digital content creation and media production, providing opportunities for individuals from diverse sociodemographic backgrounds to engage in creative activities and enhance their multimedia video content. However, less attention has been paid to recent research exploring any possible relationships between AI-generated video creation and the sociodemographic variables of undergraduate students. This study aims to investigate the multifaceted relationship between AI-generated video content and sociodemographics by examining its implications for inclusivity, equity, and representation in the digital media landscape. An empirical study about the use of AI in video content creation was conducted with a diverse cohort of three hundred ninety-eighth undergraduate ($n = 398$) students. Participants voluntarily took part and were tasked with conceiving and crafting their AI-generated video content. All instruments used were combined into a single web-based self-report questionnaire that was delivered to all participants via email. Key research findings demonstrate that students have a favorable disposition when it comes to incorporating AI-supported learning tasks. The factors fostering this favorable attitude among students include their age, the number of devices they use, the time they dedicate to utilizing technological resources, and their level of experience. Nevertheless, it is the student's participation in AI training courses that exerts a direct impact on students' ML attitudes, along with their level of contentment with the reliability of these technologies. This study contributes to a more comprehensive understanding of the transformative power of AI in video content creation and underscores the importance of considering instructional contexts and policies to ensure a fair and equitable digital media platform for students from diverse sociodemographic backgrounds.

Keywords: Artificial intelligence, Higher education, Machine learning, Sociodemographics, Video content creation

Introduction

Video content creation has become one of the most influential and rapidly expanding forms of media on various online platforms (Buckingham Shum & Luckin, 2019). Over the past decade, video content has progressively taken over consumers' experiences.

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Recent statistics reveal that 91% of internet users watch videos weekly, and they spend more than half of their daily online time engaging with video content (Fortune, 2022). To empower content creators, Artificial Intelligence (AI) integrated into video content platforms can generate both long and short videos using deep generative networks. AI-generated video platforms, such as HeyGen,[1] Synthesia,[2] and DeepBrain AI,[3] are noteworthy examples that enable individuals with no video editing skills to effortlessly create generative AI videos based solely on a script. These platforms streamline the video creation process by enabling tech-savvy instructional designers and content creators, who are well-versed in the usage of technological advancements, to transform text into videos within minutes, complete with AI-generated avatars and voices. For instance, users can input the text they want to be spoken in the video, and the generative AI will automatically produce a lifelike voice to deliver the dialogue through digital entities represented by humanistic characteristics (avatars) for narration (Farrokhnia et al., 2023).

The integration of AI-powered tools into video creation platforms has emerged as a potential solution to alleviate the production demands by assisting creators in the content creation process and making video production more accessible to the general public (Huang et al., 2023). Generative AI, which can create new digital content, is fundamentally changing the creative landscape by focusing on generating content that is not explicitly programmed. It also refers to a class of AI techniques that focus on generating content, such as text, images, or even music, using machine learning models. These models are trained on vast datasets and learn to generate new, creative content that often mimics human-produced work (Baidoo-Anu & Ansah, 2023). Generative AI technologies have also found applications in fields like report generation and learning materials reproduction, which were traditionally considered the exclusive domain of human experts (Liu, 2023). Moreover, there is growing interest and widespread knowledge regarding the impact of generative AI on the productivity and creative processes of content creators on online video platforms. Given the growing significance of video content in online consumer experiences, it is crucial to comprehend how generative AI will reshape online video platforms and the creative industries at large (Fuchs, 2023; Meyer et al., 2023).

Machine Learning (ML) and Natural Language Processing (NLP) technologies, which are widely utilized in AI platforms, have become integral parts of our digital landscape, influencing various aspects of daily life (Chen & Zhai, 2023). The rapid advancement of AI and ML technologies has not only transformed the way we interact with digital platforms but has also raised fundamental questions about the societal implications of these technologies (Pataranutaporn et al., 2021; Rahman et al., 2023). Moreover, the impact of AI-generated video creation on sociodemographics is a multifaceted phenomenon with far-reaching implications. AI-powered content creation has the potential to democratize media production, making it accessible to individuals and groups from diverse sociodemographic backgrounds. It can lower barriers to entry for aspiring creators and provide opportunities for

[1] https://app.heygen.com/.

[2] https://www.synthesia.io/.

[3] https://www.deepbrain.io/.

underrepresented voices to be heard (Monkam & Yan, 2023). Consequently, understanding how individuals from diverse sociodemographic backgrounds perceive and utilize such technology is crucial for designing user-centric applications, ensuring equitable access, and shaping responsible and equitable AI deployment (Wang et al., 2023).

However, the use of AI in video creation also raises concerns about its potential to perpetuate existing sociodemographic biases. If AI algorithms are not carefully designed and trained on diverse datasets, they may inadvertently replicate societal prejudices and reinforce stereotypes in the content they generate (Ch'ng, 2023). Therefore, it is crucial to strike a balance between harnessing the creative potential of AI-generated videos and ensuring that these technologies are developed and deployed with a keen awareness of their impact on sociodemographic inclusivity and equity (Rahman & Watanobe, 2023). Thus, the impact of AI-generated video creation on sociodemographics presents a compelling area for research, with several notable research gaps that merit investigation. While AI has the potential to support content creation and amplify diverse voices, there is a notable scarcity of studies that delve into how AI-driven video production technologies specifically affect marginalized or underrepresented sociodemographic groups (Kuhn et al., 2023; Velander et al., 2023). Understanding whether AI-powered platforms facilitate greater inclusivity and representation or, conversely, exacerbate existing disparities in sociodemographics is a critical research gap. Additionally, there is limited research examining the role of sociodemographic factors, such as age, gender, previous participation in AI training courses, in shaping both the consumption and perception of AI-generated video content creation (Zhou et al., 2023; Xia et al., 2022). Investigating how these factors intersect with individuals' attitudes, preferences, and trust in AI-generated content can provide valuable insights into the broader societal impact of this technology, helping inform ethical and policy considerations in the digital media landscape.

Addressing the above-mentioned research gap can contribute to a more comprehensive understanding of how AI-generated video content intersects with sociodemographics and its implications for media diversity and representation. Hence, the research questions (RQs) that this study seeks to answer are as follows:

> *RQ1: Which sociodemographic factors affect the essential skills required for the development of effective learning tasks and projects related to AI-generated video creation?*
> *RQ2: How do the interrelationships between different constructs impact students' attitudes in designing and developing learning tasks with AI-generated video creation?*

To answer the above RQs, this study has a twofold purpose: (a) to examine the attitudinal inclination of undergraduate students from diverse academic backgrounds across the globe toward implementing AI-supported practices to design, develop, and apply their learning projects in different disciplines, and (b) to investigate sociodemographic factors affecting students' attitudes in the context of fostering AI-generated video content creation and practices in tertiary education.

Background

AI is increasingly being used in education, having a significant impact on teaching and learning. It is the field of computer science that deals with the creation of intelligent agents, which are systems that can reason, learn, and act autonomously. Additionally, learning is a critical aspect of AI, as it allows intelligent agents to improve their performance over time and adapt to new situations (Wang et al., 2023). To provide a more detailed explanation of the relationship between learning and AI, it is important to highlight some of the most well-known potentials. First, AI can transform traditional educational methods by offering personalized learning experiences. It can analyze the unique needs and abilities of each student, adapt content accordingly, and provide real-time feedback. This adaptability enhances the learning process by catering to individual learning styles and pacing (Chen & Zhai, 2023). Second, AI can offer personalized content recommendations, adaptive quizzes, and assessments, making learning more engaging and effective. It can also identify areas where a student might be struggling and provide targeted resources or interventions to address those challenges (Baidoo-Anu & Ansah, 2023). Third, AI can facilitate the creation of online learning platforms and resources, making education more accessible to a wider audience. It can automate administrative tasks, making education more cost-effective and efficient. For example, AI chatbots can provide instant support to students, and automated grading systems can reduce the workload on educators (Sarker, 2022). Fourth, AI technologies can analyze vast amounts of educational data to identify trends and patterns in learning. This data-driven approach can inform educators and institutions about the effectiveness of their teaching methods, helping them refine their strategies (Aldoseri et al., 2023).

AI-generated video content has made remarkable progress in recent years, transforming media production and consumption in many ways. Both AI and ML technologies have played a pivotal role in the creation of highly convincing synthetic videos. One prominent application is video content creation, which leverages NLP to superimpose one person's face onto another's in multimedia footage, giving the illusion of realistic impersonation (Velander et al., 2023). Furthermore, AI has enabled the emergence of virtual influencers, entirely computer-generated characters that engage with audiences on social media platforms and in advertising campaigns. These virtual personas are meticulously crafted to be visually appealing and relatable, blurring the lines between human and AI-generated content (Xia et al., 2022). As AI continues to enhance video content creation, addressing concerns related to the authenticity and ethical use of these technologies remains a critical challenge for researchers and policymakers alike (Whittaker et al., 2020). While this technology has garnered significant attention for its potential in filmmaking and entertainment, it has also raised ethical concerns due to its misuse in spreading misinformation and creating fraudulent content (Adeshola & Adepoju, 2023).

To date, AI-generated platforms for content creation have brought many changes in higher education. Pataranutaporn et al. (2021) explored the advancements in machine learning that enable the creation of hyper-realistic AI-generated media, including characters with synthesized faces, bodies, and voices. While ethical concerns have dominated discussions, the perspective emphasizes the positive use cases of AI-generated characters, especially in supporting learning and well-being. The same author also emphasizes the need for ethical considerations and traceability in AI-generated media. Ch'ng (2023) discussed the impact of AI on instructional design, comparing traditional learning methods to AI-enabled approaches and highlighting potential shifts in instructional design practices. This includes the emergence of new roles, such as AI content creators and AI technology specialists, as well as the importance of understanding human–machine interactions to enhance the learning experience. Rahman et al. (2023) addressed the increasing importance of video resources in higher education and the challenges of navigating lengthy lecture videos. The same authors presented AI-driven solutions for generating visual and textual summaries of lecture video segments, improving content accessibility. The results show significant improvements in user perception and usefulness, with AI-driven summaries outperforming traditional methods. In their study, Vallis et al. (2023) explored the pervasive influence of AI and algorithms in the contemporary post-digital world. They also discussed the utilization of AI-generated avatars in educational content delivery, specifically focusing on their implementation in business ethics education. The study revealed positive student perceptions and preferences for AI-driven lecture delivery, along with the challenges associated with using AI avatars in education.

AI-generated video content allows users to generate or automate multimedia content without direct human intervention and to augment the creative process by providing tools and assistance to human content creators. Some of the most significant points of view that previous works (Pataranutaporn et al., 2021; Rahman et al., 2023; Zhou et al., 2023) have underlined the following:

1. *Automatic video generation*: AI algorithms can analyze and process large datasets of images, videos, text, and audio to generate video content automatically. For example, AI can generate videos from text descriptions, assemble stock footage and images into a cohesive video, or even create animations.
2. *Video production improvement*: AI can be used to improve the quality of existing video content. This includes tasks like upscaling video resolution, removing noise, and improving color grading in scenes.
3. *Content recommendation*: AI algorithms are used to recommend video content to users based on their viewing history, preferences, and behavior. This personalization can improve user engagement on platforms like streaming services and social media.
4. Automated video content editing: AI-powered video editing tools can automatically select and arrange clips, apply transitions, add music, and even generate subtitles, making the video editing process more reliable and efficient.
5. *Visual effects and speech synthesis*: AI can assist in the creation of visual effects and animations in videos, including generating 3D models, simulating physics-based animations, and adding special effects. AI can generate synthetic voices and speech, allowing for voiceovers, dubbing, or narration in videos.

A growing number of studies (Adeshola & Adepoju, 2023; Cooper, 2023; Kasneci et al., 2023; Wang et al., 2023) have additionally highlighted the transformative impact of AI on various educational settings, from instructional design and content creation to improved accessibility and engagement in learning, suggesting a number of crucial potentials and drawbacks. On the one side, the benefits of AI-generated video content:

1. Efficiency: AI can generate video content at a faster pace than humans. This can be especially advantageous for industries like animation and visual effects, where creating complex scenes and effects can be time-consuming.
2. Cost savings: AI can significantly reduce production costs by automating various aspects of video creation, such as animation, special effects, and editing, which would otherwise require a large team of human experts.
3. Accessibility: AI-generated video content can democratize media production, making it more accessible to individuals and smaller organizations who may not have the resources for traditional production methods.
4. Creative exploration: AI can generate novel and imaginative content, leading to creative exploration in areas like art, storytelling, and virtual worlds.

On the other side, the drawbacks of AI-generated video content are as follows:

1. Ethical concerns: AI-generated videos, particularly deepfakes, can be used for malicious purposes, including misinformation, impersonation, and privacy invasion. This raises significant ethical and legal concerns.
2. Bias and fairness: AI models trained on biased data may perpetuate stereotypes and biases in generated content. Ensuring fairness and diversity in AI-generated content remains a challenge.
3. Quality and authenticity: While AI has made great strides, the quality and authenticity of AI-generated content can still fall short of human-created content, particularly in terms of emotional depth and nuanced storytelling.
4. Depersonalization: In some cases, the use of virtual influencers and AI-generated characters may contribute to a sense of depersonalization in media, as audiences interact with non-human entities instead of real individuals.

Balancing the benefits and drawbacks of AI-generated video content requires careful consideration of ethical, legal, and societal implications, as well as ongoing research and development to address the challenges associated with this technology. Understanding these sociodemographic influences on AI platform usage is vital for developers, policymakers, and researchers. It can help in addressing biases, improving user experiences, and ensuring equitable access to AI technologies. Moreover, recognizing these factors can aid in tailoring AI platforms to be more inclusive and culturally sensitive, fostering a more positive and productive relationship between individuals across diverse sociodemographic groups.

Research method

Research context

Empirical research is one of the most reliable types of research that empowers researchers to exercise control over various research variables, ultimately leading to the attainment of the most pertinent research results (Cohen et al., 2002). Empirical investigations play a crucial role in uncovering causal relationships between variables, illuminating how changes in one element can influence changes in another, thereby offering crucial insights for understanding complex phenomena and informing well-informed decision-making. Additionally, this type of research often forms the foundation for policymaking, especially in fields like social sciences, serving as the cornerstone on which instructors and researchers can rely to shape decisions with far-reaching consequences for communities and societies at large (Scott, 2005). As such, this empirical study engaged undergraduate students from different parts of the world who willingly took part and utilized AI-generated video content to design, create, and apply their educational projects.

Participants

A total of three-hundred and ninety-eight responses ($n = 398$) from willing participants were collected, which were subsequently utilized for analysis. Among these respondents, 184 self-identified as female, making up 46% of the total, while 214 identified as male, constituting the remaining 54%. The average age of the participants was 21.6 years, with a standard deviation of 2.7, ranging from 20 to 24 years old. The participants were classified as follows: 155 were seniors, accounting for 39% of the sample; 122 were juniors, comprising 31%; 100 were sophomores, making up 25%; and 39 were freshmen, representing 10%. These individuals pursued various academic disciplines, including computer science (n = 193), language acquisition (n = 53), instructional design/pedagogy (n = 21), chemistry (n = 13), mathematics (n = 55), physics (n = 19), administration (n = 123), business (n = 53), and interactive media literacy (n = 44).

Procedure

This study investigates the viewpoints of undergraduate students regarding the use of AI-generated video content creations in diverse educational fields. The primary goal of this research was to assemble a random and representative sample of participants from various geographical regions. In the initial phase of the survey, participants' past experiences were collected, regardless of their specific academic disciplines. The research subjects were selected from two well-established email lists commonly used by instructors and students to exchange ideas, and solutions or engage in experiments/projects involving AI-generated video content creations. These email lists regularly distributed announcements. The survey was distributed to a group of 467 students located in different global regions using email as the distribution method. Out of these, 398 valid responses were obtained, resulting in a robust 85% response rate. Students who did not follow the prescribed guidelines for completing the entire questionnaire were excluded from the survey analysis (Fig. 1).

Completing the entire set of questionnaires required no more than 60 min. It is of great importance to highlight that the questionnaire deliberately avoided categorizing participants as novice or expert users. This approach was intentionally chosen to gain a comprehensive understanding of students' experiences with AI-generated video content creation. Consequently, the survey did not differentiate participants' responses based on their expertise levels acquired through university-level courses. This methodology was selected due to the novelty of the survey and the necessity to incorporate the perspectives and experiences of all participants without discrimination. From this perspective, the surveyed participants were primarily those who used AI-generated video content: (a) to create, design, manage, modify, and ultimately apply their learning projects effectively.

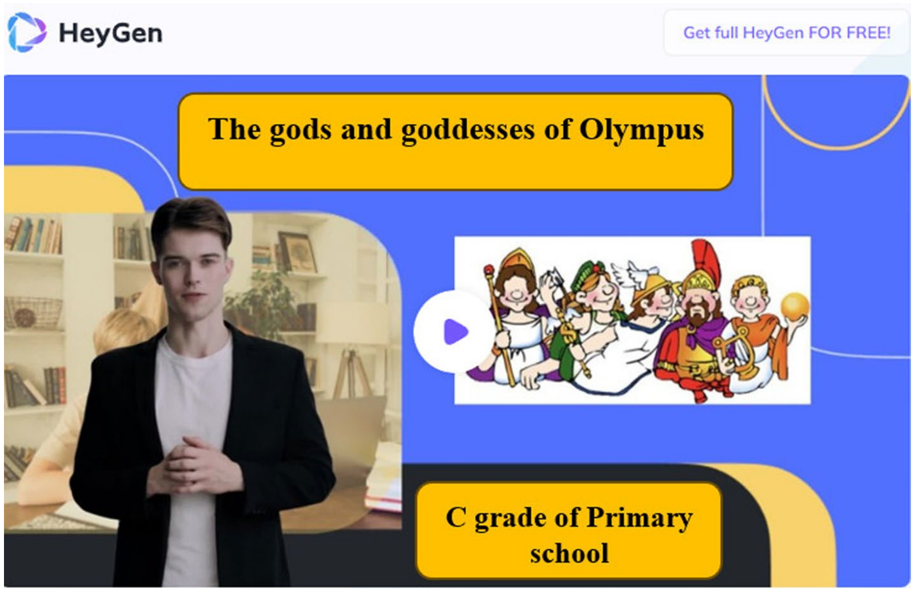

Fig. 1 An example of AI-generated video creation using HeyGen platform

These projects included generating presentations, coding, or artifacts for interaction with learning management systems or online resources, serving both formal and informal professional advancement purposes, (b) to utilize advanced technological resources and services related to the learning process, and (c) to engage in various activities aligned with departmental interests, enabling the exchange of ideas beyond their existing responsibilities.

Participants who wanted to share their experiences related to AI-generated video content creation should contribute to the existing body of knowledge considering the practical applications, societal implications, and future trends to make their projects relevant and impactful. Some potential viewpoints that could allow participants to fill this study's research questions are as follows:

- Investigate the current state of AI-generated video content, including virtual avatars, video content, voices and AI-generated animations.
- Research the latest advancements in AI-based video summarization techniques that can automatically generate concise summaries of long videos.
- Examine AI algorithms used by platforms like YouTube and Netflix to personalize video recommendations for users.
- Explore how AI can enhance the video editing process by automating tasks like scene segmentation, color grading, and audio enhancement.
- Investigate AI-driven video compression techniques that aim to reduce bandwidth requirements while maintaining video quality.

Two significant factors influencing students' participation in this study were: (a) all sessions were aligned with a 20-week university calendar, covering both the winter and spring semesters (from October 2022 to August 2023), following the standard 25-week academic period commonly observed by most universities, and (b) the use of

AI-generated video tools was adopted as an alternative platform for completing their learning projects.

Instrumentation

The questionnaires were accessible online and administered via email to all participants. To ensure cross-cultural comprehension, all subscales were carefully translated into English, given its widespread global usage. Participants then provided their responses using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). More specifically, the Machine Learning Attitude Scale (MLAS) was used to investigate how university students view machine learning, and it underwent validation by Hopcan et al. (2023). This scale comprises 39 items, which are grouped into six different sub-categories. These categories include interest in technology (IT), understanding the importance and impact of technology (IIT), contemplating career options related to technology (TRCP), integrating technology into creative pursuits (TCA), the convergence of technology with educational courses (TC), and perceptions regarding the gender roles associated with technology (GRT). In terms of reliability, Cronbach's alpha coefficient was determined to be 0.844, which is considered acceptable according to the standards set by Cortina (1993).

The Kaiser–Meyer–Olkin test produced a significant result (KMO = 0.909), indicating the suitability of the data for factor analysis. Additionally, the Bartlett test of sphericity demonstrated a strong outcome ($\chi^2 = 1923.669$; df = 255; $p < 0.001$), further supporting the data's appropriateness for factor analysis. Following both exploratory and confirmatory factor analysis, this instrument can be considered a valid tool for gathering information. Specifically, eight sociodemographic variables were included: gender, age, general ICT usage, appropriateness of AI-generated video content creation, number of devices used for AI-generated content access and creation, participation in AI training courses, time–frequency analysis of AI platform use, and tech-savviness (Table 1).

Ethical considerations

To ensure a comprehensive and diverse group of participants, the researcher(s) utilized purposive sampling, a method chosen to encompass a wide range of experiences across various academic disciplines and levels of digital proficiency. This deliberate selection aimed to mitigate any potential disparities in digital skills among participants, thus maintaining the study's experimental validity even without random selection, following the recommendations outlined by Adeshola and Adepoju (2023). The same authors found that participants of different genders exhibited no significant differences in their access to and use of Information and Communication Technology (ICT). This step was taken to reduce potential biases, enhance the study's internal validity, and minimize the influence of external variables. Each participant shared similar backgrounds in terms of ICT usage, and their demographic characteristics, encompassing socio-economic and socio-cultural dimensions, were standardized throughout the study. Specifically, all participants had substantial experience with AI-generated video content creation. The digital survey was conducted towards the end of the spring semester, specifically between weeks 13 and 15.

Table 1 Sociodemographic data of the participants

Variables	n	%
Age		
18–19	94	30.9
20–21	154	46
22–23	82	19.3
+23	48	3.9
General ICT use		
Yes	295	65.9
No	103	34.1
Appropriateness of AI-generated video content creation		
Yes	370	75.2
No	28	24.8
Number of devices used for AI-generated content access and creation		
0	6	1.1
1–4	114	32.9
5–7	193	49.7
+8	85	16.2
Participation in AI training courses		
0–1 course	125	39.9
2–5 courses	196	47.9
More than 5 courses	67	12.3
Time–frequency analysis of AI platform use		
1–2 h	207	40.7
3–4 h	170	32.7
5–6 h	56	15.8
+6 h	45	10.8
Tech-savviness		
Highly tech-savvy (1–10 years)	0	11.4
Slightly tech-savvy (less than 10 years)	130	34.1
Moderately tech-savvy (less than 5 years)	114	20.3
Not tech-savvy (No experience)	154	34.2

Stringent ethical considerations regarding participant welfare were diligently observed throughout this study as Winter and Gundur (2022) have pointed out. These measures included obtaining informed consent, ensuring confidentiality and anonymity, and safeguarding the well-being and privacy of the participants. Voluntary participation was the sole method of involvement, and prior to data collection, all participants provided informed consent. Before introducing the instructional intervention, a comprehensive explanation of the study's objectives was provided to students in both groups. Additionally, they were required to endorse a consent document outlining: a) potential consequences associated with the use of assessment platforms; b) the collection and handling of their data in accordance with the General Data Protection Regulation (GDPR) provisions; and c) the participants' unrestricted right to withdraw from the study at any time without facing adverse consequences. Confidentiality was highly prioritized, with no collection of Internet Protocol (IP) addresses once the survey was conducted.

Data collection

All instruments used were combined into a single web-based self-report questionnaire that was delivered to all participants via email. Data was collected from all participants through online questionnaires in English due to its global prevalence. The he researchers first contacted instructors or supervisors via email to obtain consent for involving students enrolled in university courses and permitting students to use AI platforms for their projects. After obtaining the necessary approvals, recruitment letters and survey links were shared on message boards, with instructors actively encouraging student participation. Students who volunteered participated by completing online consent forms, followed by the survey itself on a designated website. Online consent was mandatory, indicating their comprehension and agreement to take part.

Participants were explicitly informed of their right to withdraw from the study at any time, without encountering any adverse repercussions. The study was conducted voluntarily, with all participants giving informed consent before data collection. Participation in the teaching intervention did not offer any extra grading incentives, nor did withdrawal result in any grade deductions. The privacy of participants' identities was strictly maintained, with no mention of names in the data collection. Each participant was assigned a distinct identification number for research purposes, and all associated information was securely held by the main researcher.

Following the guidance provided by Vahedi et al. (2023), there were additional points provide a more comprehensive overview of the data collection process, emphasizing the importance of data analysis planning. These are as follows:

1. *Data security:* Given that data was collected online, it was important to highlight security measures to protect the confidentiality and privacy of the participants, ensuring that personal information is stored safely, and following data protection regulations to protect participants' sensitive data.
2. *Data quality assurance*: To maintain the quality of the collected data, the research team might have employed various strategies, such as setting up validation checks in the online questionnaires during the data collection phase. Ensuring data accuracy and reliability is crucial for the validity of research findings.
3. *Data management*: A proper data management plan established to organize and store the collected data. This includes decisions about data storage duration, backup procedures, removing incomplete or duplicate responses for data analysis.

Data analysis

The acquired data was thoroughly analyzed with SPSS 27.0 and AMOS 24.0. For each variable, descriptive statistical measurements were used, as well as reliability testing. Although performing a path analysis cannot by itself prove a causal link between variables, it does give researchers a way to look at potential path models, enabling the identification of both direct and indirect effects among the variables under consideration (Jaccard & Turrisi, 2003). Furthermore, the approach of this study is significant since it combines the investigation of sociodemographic effects into a single analysis, effectively harmonizing with existing theoretical constructs and empirical evidence. Prior to undertaking the assessment, a centering technique was conducted to all variables to avoid any difficulties associated to multicollinearity (Kyriazos, 2018). The specified significance level for the entire analysis was set at.05. To assess these total scores, descriptive statistics (Mean: M; Standard Deviation: SD) were used.

Results

The study found that 72.63% of undergraduate students displayed a positive attitude towards the use and development of AI-supported video content in their teaching and learning processes. This conclusion is drawn from the fact that this percentage of students scored above 85% on the assessment tool used in the study, surpassing the threshold of 82.25 out of a total of 132 points. This indicates a substantial number of students who are well-prepared and open to incorporating AI into their educational practices.

Table 2 presents the average scores achieved in various sociodemographic categories and examines whether significant differences exist within each of these categories.

Regarding gender, no statistically significant differences were observed ($p = 0.147$). In this context, males had a slightly higher mean score ($M = 88.36$; $SD = 6.77$) compared to females ($M = 87.50$; $SD = 6.11$). Statistical significance was found concerning age ($p = 0.001$), where subjects over the age of 65 had a higher mean score ($M = 92.86$; $SD = 4.02$) compared to other age groups.

Concerning the general ICT usage, no statistically significant differences were detected ($p = 0.216$), with students who utilized ICT in their teaching and learning processes having slightly higher mean scores than those who did not. Similarly, no statistical significance was observed among students who viewed AI as a suitable platform. In this case, those who held a positive opinion had slightly higher mean scores than those who did not. In terms of the number of devices, significant differences were found ($p = 0.035$), with students who had between one and four devices showing the highest mean score ($M = 88.99$; $SD = 6.52$) compared to others. Conversely, completing training courses related to ICT did not demonstrate a significant relationship. Participants who had completed between two and five ICT courses had a slightly higher average compared to others ($M = 88.18$; $SD = 6.22$).

However, the time spent by students on technological devices in their daily lives was found to be significant ($p = 0.001$), with those who used technological resources for 1–2 h per day having a higher average score ($M = 89.02$; $SD = 6.74$) than others. Lastly, AI experience also showed significance, with students having less than ten years of experience having a higher mean score ($M = 90.51$; $SD = 8.36$) than their more experienced counterparts.

To construct the structural equation model (SEM), particularly the path analysis model, we have assessed the goodness-of-fit indices for the statistical analysis, as shown in Table 3. The computed coefficients are below 288, which suggests that the values are appropriate (Watkins, 2021). Subsequently, the fit indices for the models to determine their adequacy was examined. After making several adjustments in both cases, they were deemed suitable, aligning with all the specified assumptions (Kyriazos, 2018).

Table 2 Descriptive statistical data and differences between groups

	n	M	SD	p
Gender				
Man	157	88.36	6.77	.147
Woman	241	87.50	6.11	
Age				
18–19	94	88.36	7.11	.001
20–21	154	87.23	6.06	
22–23	82	85.46	5.49	
+24	48	92.86	3.02	
General ICT use				
Yes	295	88.14	6.48	.2 16
No	103	87.34	6.25	
Appropriateness of AI-,generated video content creation				
Yes	370	88.06	6.37	.222
No	28	17.16	6.50	
Number of devices used for.AI-generated content access and creation				
0	6	84.00	5.11	.035
1–4	114	88.99	6.52	
5–7	193	87.54	6.37	
+8	85	86.75	6.08	
Participation in AI training courses				
0–1course	125	87.72	6.62	.480
2–5 courses	196	88.18	6.22	
More than 5 courses	67	87…09	6.46	
Time–frequency analysis of AI platform use				
l-2 h	207	89..02	6.74	.001
3–4 h	170	86.53	5.87	
5 h	56	87.16	5.67	
+6 h	45	86.40	6.07	
Tec.h-savviness				
Highly tech-savvy (1–10 years)	0	.00	.00	.001
Slightly tech-sav y (less than 10 years)	130	87.78	6.27	
Moderately tech-savvy) (less than 5 years)	114	86…26	5.68	
Not tech-savvy (No experience)	154	87.90	6.31	

n sample, *M* mean, *SD* standard deviation, *p* p-value

In the path analysis model, it was examined how various sociodemographic variables influence students' attitudes toward the use of ML and AI technologies in teaching and learning. The results reveal that only participation in AI training courses for content access and creation demonstrates a significant relationship with students' attitudes toward AI and ML utilization. However, in the remaining established connections, no significant relationships were observed in Table 4.

The path model illustrates the connections established between sociodemographic variables and students' attitudes toward the integration of AI in teaching and learning processes. In this model, attitudes regarding AI usage dwell in the central position, indicating the impact of sociodemographic variables on these attitudes. As depicted in Fig. 2, only participation in AI training courses exerts an influence on the attitudes

Table 3 Goodness and fit indices of the analysis models

Fit index	Obtained value		Expected value
	Path 1	Path 2	
x^2	71.022	14.224	
Df	18	33	
x^2/df	1.89	24 1	< 3
	4		
GFI	.820	.855	.90–1
AGFI	.801	.824	.90–1
RMR	.076	.072	Closest to 0
RMSEA	.039	.036	< 0.05
CFI	.821	.811	.90–1
NFI	.819	.801	.90–1
NNFI	.828	.811	.90–1

GFI goodness of fit index, *AGFI* weighted fit index, *RMR* root means square residual index, *RMSEA* root means square error of approximation, *CFI* comparative fit index, *NFI* normalized fit index, *NNFI* non-normalized index of fit

Table 4 Path analysis model

Relationships between variables	RW	SE	CR	p	SRW
MLAS ← Gender	– .041	.018	– 1.718	.069	– .076
MLAS ← Age	.028	.019	1.819	.055	. 092*
MLAS ← General ICT use	– .10	.024	– 0.477	.556	–.026
MLAS ← Appropriateness of AI-generated video content creation	– .19	.026	– 0.688	.426	–.034
MLAS ← Number of devices used for AI-generated content access and creation	– .012	.013	– 1.355	.142	– .065*
MLAS ← Participation in AI training courses	– .043	.015	– 2.763*	.004	– .132*
MLAS ← Time–frequency analysis of AI platform use	– .008	.012	– 0.308*	.683	– .017*
MLAS ← Tech-savviness	– .018	.015	– 1.123	.257*	– .053

RW Regression weighting, *SE* Standard error; *CR* Critical radio, *SRW* Standardized regression values, *$p < .001$ significance relationship

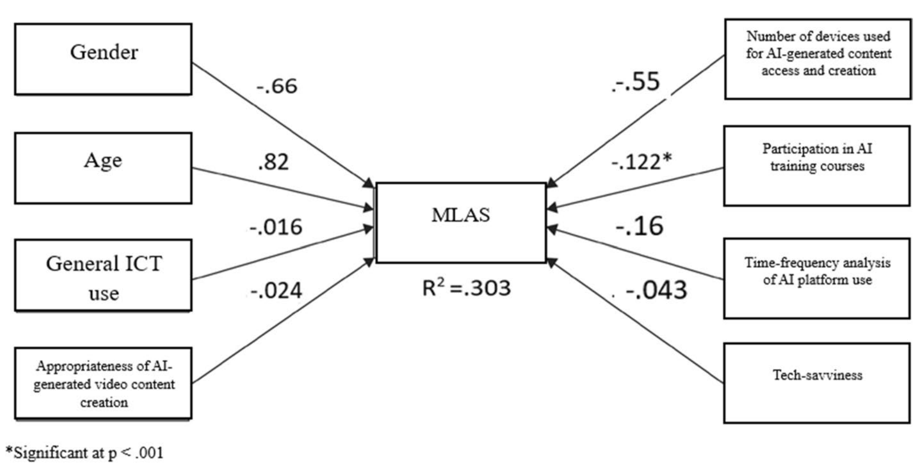

Fig. 2 Illustration of the path analysis model

of these educators toward ML and AI technologies utilization. None of the other variables have any discernible impact. In this vein, the configured model explains 30.3% of the variance in attitudes towards machine learning and AI.

Discussion

AI and ML technologies embrace the promise of supporting digital content creation and media production, offering various opportunities for undergraduate students from diverse sociodemographic backgrounds to engage in creative endeavors and amplify their multimedia video content. Nevertheless, less attention has been paid to recent research exploring the dynamic intersection between AI-generated video creation and undergraduate students' sociodemographic variables, shedding light on both the transformative potentials and challenges within this growing field. The findings of this study provide insights from empirical evidence on the complex interplay between sociodemographic variables and students' attitudes toward the integration of ML and AI in generating video and content for teaching and learning procedures. Similarly, when considering attitudes toward the use of ML, the influence of sociodemographic variables was explored. Understanding these relationships is crucial for shaping educational policies and practices that effectively leverage these technologies.

Regarding the RQ1, the analysis of the current study indicates that among the various sociodemographic factors examined, only participation in AI training for content access and creation exhibited a significant relationship with students' attitudes toward ML technology. These findings come in line with previous studies (Adeshola & Adepoju, 2023; Ch'ng, 2023), which suggested that targeted training programs aimed at enhancing students' competencies in utilizing AI technologies may be effective in fostering positive attitudes and, consequently, greater acceptance. In this context, only students' training in the use of AI demonstrated a significant influence on their attitudes toward ML. This highlights the importance of AI training in preparing students to effectively incorporate AI technologies into their teaching practices. Interestingly, the remaining sociodemographic variables examined in both MLAS and AI-supported instructional contexts did not show any significant influence on students' attitudes. This suggests that factors such as gender, age, AI experience, and the number of devices owned by students did not directly impact their attitudes toward these emerging technologies. These findings align with the notion that attitudes toward technology adoption are complex and multifaceted, often influenced by individual experiences, perceptions, and pedagogical beliefs.

In regard to RQ2, this study's statistical analyses reveal that there are not any statistically significant differences concerning age, the number of devices students use daily, their time commitment to technological resources, and ICT usage. To this end, students aged over 25, those using approximately 1 to 4 devices, students with less than 10 years of experience, and those dedicating 1 to 2 h daily exhibited the most favorable attitudes. Essentially, these factors are considered crucial in the adoption of AI in various video-supported instructional tasks. Previous studies (Huang et al., 2023; Rahman et al., 2023) acknowledged age and experience as key factors for effective AI utilization but emphasize lower values for these factors as more influential. In particular, the contrast between students' years of service and their experience is quite striking. It can be inferred that sociodemographic variables like gender, age, appropriateness of AI-generated video content creation in instructional support, and number of devices do not significantly impact students' propensity to exhibit positive attitudes towards ML technologies. These findings were obtained by examining the relationship between good attitudes toward AI use and each sociodemographic variable individually. In contrast, others (Vallis et al., 2023; Velander et al., 2023) considered gender and ICT usage frequency as factors affecting students' digital competence levels, consequently deeming them determinants for potential AI technology adoption. Other studies (Kasneci et al., 2023; Wang et al., 2023) directly explored students' characteristics for AI usage suggesting that participation in AI training courses frequency directly influences a positive evaluation of AI as a potential "tool" in teaching and learning. In this context, the initial path analysis indicates a direct impact of AI training courses on students' attitudes towards AI use, suggesting that their participation does indeed play a role in the overall model. Additionally, other researchers (Cooper, 2023; Cotton et al., 2023) have underscored the importance of techno-pedagogical training for students in achieving optimal AI-mediated methodologies, emphasizing a higher frequency of use among educators with greater digital competence levels. The findings of this study indicate that less than half of a diverse cohort consisting of 398 undergraduate students from a wide array of disciplines across the globe who took part have a positive attitude towards AI and ML technologies. It also seemed that individuals at a younger age use more devices, and those who have participated in AI training courses are more likely to have positive attitudes. These findings indicate that students' attitudes towards AI can be improved by providing them with training sessions on learning someone better how to utilize this contemporary technology and its tools as well as by ensuring that they have access to reliable AI resources. This highlights the need for efforts to improve students' attitudes, such as providing training sessions and ensuring access to reliable AI resources.

Implications

The outcomes of this study provide several implications for educational practitioners, policymakers, and researchers. The study's diverse cohort of undergraduate students from various disciplines and countries suggests that these findings have relevance on a global scale. The implications of the study could inform AI education policies and practices worldwide. First, the significance of previous training courses for enhancing attitudes toward MLAS and fostering their positive attitudes toward AI-generated video content highlights the importance of continued professional development in these domains. Investing in targeted training programs could be a crucial approach to encourage technology integration in educational settings. This study indicates a direct impact of ICT training on students' attitudes towards AI use, suggesting that participation in such courses plays a role in shaping students' perceptions of AI. Educational institutions should consider integrating ICT training into their curricula. Second, the limited influence of other sociodemographic variables suggests that a more nuanced understanding of students' attitudes is needed. Lastly, as the explained variance in attitudes toward MLAS and AI was relatively low, it is evident that other unexamined factors play a substantial role in shaping students' attitudes.

The current study highlights several pedagogical implications, particularly in the context of learning and teaching related to ML and AI for video content creation. First, this study underscores the significance of prior training courses in enhancing undergraduate students' attitudes toward MLAS and fostering positive attitudes toward AI. This finding implies that continuous professional development and training are essential for educators. Educators need to stay updated with the latest advancements in technology, especially in domains like ML and AI. This will enable them to effectively teach and integrate these technologies into the educational process. The implication here is that investing in targeted training programs for teachers and instructors can be a pivotal approach to encourage the integration of technology into educational settings. By enhancing educators' knowledge and attitudes toward these subjects, they can, in turn, influence their students more effectively. Second, the study also demonstrates a direct impact of ICT training on students' attitudes toward AI use. This implies that participation in ICT courses can play a significant role in shaping students' perceptions of AI. Therefore, educational institutions should consider integrating ICT training into their curricula. This integration can help students not only become proficient users of technology but also develop a positive and informed attitude towards AI. By incorporating ICT training as a fundamental part of the educational experience, institutions can prepare students for a technology-driven future. Third, the limited influence of sociodemographic variables on students' attitudes toward MLAS and AI suggests that a more nuanced understanding is necessary. In education, it's essential to recognize that students come from diverse backgrounds, and their attitudes and perceptions may not be solely determined by their demographic characteristics. Educators and institutions should take a more comprehensive approach to understand and address the unique needs and perspectives of each student. This means adopting teaching strategies and curriculum designs that are adaptable and responsive to individual differences and experiences. Fourth, it is of great importance to prepare students for a technology-driven world. Educators should design interdisciplinary curricula that allow students from different academic backgrounds to collaborate and apply MLAS and AI in various fields. This approach can foster creative problem-solving and real-world application of these technologies. Additionally, this study's global relevance highlights the importance of cultural sensitivity and global education. Educators should incorporate diverse perspectives and global examples when teaching MLAS and AI to ensure that students have a comprehensive understanding of the global impact of these technologies. This approach promotes cultural awareness and prepares students for a globalized workforce.

Conclusion

The current study highlights the significance of different aspects in shaping students' attitudes toward MLAS and AI-generated video creation. While sociodemographic factors play a limited role, a more holistic approach is required to understand the multifaceted nature of technology adoption in education, ultimately leading to more effective and informed educational practices in this contemporary age. More specifically, this study has delved into the complex interplay between AI-generated video creation and sociodemographics to understand better its transformative potential and associated challenges. The findings underscore the promise of AI in media production, enabling individuals from diverse sociodemographic backgrounds to engage in creative endeavors. Nevertheless, the empirical evidence from this study emphasizes the critical importance of addressing biases and ensuring inclusivity in AI algorithms and datasets. Likewise, this study unveils that students generally hold a favorable attitude toward incorporating ML and AI technologies into their teaching practices. Factors such as gender, age, ICT usage, appropriateness of video content creation, time, and number of devices that used for AI play roles in shaping these attitudes, with participation in AI training courses significantly influencing students' attitudes toward AI and ML technologies.

The significance of this study lies in its empirical evidence provided by the exploration of the relationship between AI-generated video content and sociodemographic variables among undergraduate students in the evolving digital media landscape. Understanding how students from different backgrounds interact with AI-generated content creation tools is crucial for educators and institutions. It also recognizes that AI and ML technologies have the potential to adequately support content creation and media production. By examining how these technologies are used by undergraduate students from diverse sociodemographic backgrounds, this study contributes to understanding whether AI can help bridge gaps in inclusivity and equity in the digital media landscape. This study contributes to a more comprehensive understanding of the transformative potential of AI in media production. It also goes beyond the technical aspects of AI and explores how it intersects with sociodemographic factors, shedding light on the broader societal implications.

Limitations and future research

This study has identified several limitations. Consequently, the results obtained in this study must be approached with caution, as they are representative of a specific context with the following to be the most noticeable:

1. Time frame: The study's duration and data collection period may have restricted the depth of insights, as attitudes and perceptions towards AI-generated video creation can evolve.
2. Geographical and cultural variations: Participants were drawn from various countries, but cultural and regional differences may not have been adequately accounted for further analysis as factors affecting the generalizability of this study's findings.
3. Self-reporting bias: The study relies on self-reported data, which can be subject to biases, such as social desirability bias, where participants may provide responses, they perceive as more socially acceptable.
4. Technology advancements: Rapid advancements in AI and technology may have outpaced the study's findings. The landscape of AI-generated content creation is continually evolving, which might affect the applicability of the results to the current state of the field. Furthermore, another reported limitation of this study is the absence of direct assessment of students' practical experience with AR. Instead, data collection relied on participants' perceptions of their past professional experiences or prior knowledge.

Future works should consider these unexplored factors to gain a more comprehensive understanding of the dynamics surrounding the integration of these emerging technologies in educational contexts. Other research should strive for larger and more diverse samples, account for cultural nuances, and continue to monitor the ever-evolving landscape of AI technology to provide more comprehensive insights into this dynamic field. Also, there are unexplored factors, such as pedagogical beliefs, technological self-efficacy, and prior experiences with ML and AI, which can inevitably provide a comprehensive picture of what drives these technologies' adoption in different disciplines of tertiary education.

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Author contributions
Only one main and corresponding author conducted all aspects of the research presented in this paper and wrote the manuscript.

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Data availability
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Research involving human participants
All procedures performed in studies involving human participants were following the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent
Informed consent was obtained from all individual participants included in the study.

Competing interests
The author declares that he has no competing interests.

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