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ADOPTION OF AI CHAT BOT LIKE CHAT GPT IN HIGHER EDUCATION IN INDIA: A SEM ANALYSIS APPROACH

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Applications of artificial intelligence have grown to be one of the most important and well-known targets for nations in the modern era, particularly in the education sector. This is because these technologies have the potential to boost productivity and help the sector develop quickly by presenting scientific information to students in an appealing manner. To explore the link between latent variables, structural equation modeling is done using the partial least square technique structural equation model (PLS-SEM) with the help of Smart PLS. The intent of this investigation is to offer empirical support and explain the variables that may influence the adoption of artificial intelligence in higher education. The finding suggests that the hedonic, gamification, and motivational factors, as well as the convenience and efficiency factors, all have a significant impact on the adoption of artificial intelligence in India, like Chat GPT.

Keywords: *Artificial Intelligence, Higher Education, Chat GPT, SEM model, Chat bot.*

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Применение искусственного интеллекта в современном мире стало одной из важнейших национальных задач, особенно в сфере образования. Такие технологии обладают потенциалом для повышения производительности и ускоряют развитие сектора, предоставляя научную информацию студентам в интересной, привлекательной форме. Для исследования взаимосвязей между скрытыми переменными, при моделировании структурных уравнений был использован метод частичных наименьших квадратов (PLS-SEM) с помощью Smart PLS. Цель исследования – предложить эмпирическую поддержку и объяснить переменные, которые могут повлиять на внедрение искусственного интеллекта в высшем образовании. Полученные данные свидетельствуют о том, что В Индии значительное влияние на внедрение технологий искусственного интеллекта, аналогичных Chat GPT, оказывают факторы гедонизма, геймификации, мотивации, удобства и эффективности

Ключевые слова: *искусственный интеллект, высшее образование, Chat GPT, SEM-модель, чат-бот.*

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Introduction

Higher education is one of the industries where artificial intelligence (AI) is flourishing. Applications of artificial intelligence (AI) are becoming important for higher learning institutions, whether it is for individualized instruction, automated evaluation, intelligent learning environments, or supporting faculty. They provide assistance that minimizes costs and improves academic outcomes. Artificial intelligence-powered software programs called chatbots may simulate human communication interactions (J.C. Lin, et al., 2023).

Due to their extensive language training, they can respond to a wide range of queries. The use of chatbots like ChatGPT and Google Bard can be beneficial for a variety of educational institutions, from elementary and secondary schools to higher education institutions and professional organizations (J.C. Lin, et al., 2023). One of their best suits is their ability to offer customized instruction (Al-Sharafi, M. A., et al., 2022)

Artificial intelligence is a multidisciplinary area with a wide range of applications and difficulties. While developing and using AI, ethical issues must be taken into account. That requires a synthesis of expertise in computer science, mathematics, and cognitive science (Russell, S., & Norvig, P., 2016). AI highlights the necessity of enormous-scale datasets along with processing resources for efficient deep learning (LeCun, Y, et al., 2015). Bostrom analyses several ways to build superintelligence, the potential risks it poses to civilization, and measures to assure its secure growth (Atlas, S., 2023). The study emphasizes the need of giving safety and ethical issues significant thought when developing artificial intelligence. Superintelligent AI development has an opportunity to have a significant influence on humans, both favourably and unfavourably (Bostrom, N., 2014).

Chat GPT

The popularity of Chat GPT has recently increased to unprecedented heights. The OpenAI, AI Research, and deployment company is the owner and developer of Chat GPT. Several well-known individuals, including Elon Musk, Sam Altman, Peter Thiel, OpenAI's founder scientist Ilya Sutskever, Jessica Livingston, and LinkedIn cofounder Reid Hoffman, created the company, which has its headquarters in San Francisco (Atlas, S., 2023).

The first model in the GPT (generative pre-trained transformer) series, GPT-1, which was released in June 2018, included 117 million parameters. Using books as training material to anticipate the next word in a phrase, the GPT-1 language comprehension test showed the effectiveness of independent learning in interpreting tasks. With 1.5 billion parameters, GPT-2, which was launched in February 2019, represents a considerable improvement. It created cohesive, multi-paragraph prose and demonstrated a significant increase in text-generating skills. GPT-2, however, was not initially made available to the public owing to the possibility of abuse. Ultimately, the model was released in November after OpenAI carried out a gradual rollout to assess and reduce potential dangers (Banik, S., & Gao, Y. 2023). GPT-2 demonstrates the promise of autonomous multitask learning in natural language processing by learning to accomplish many linguistic tasks without explicit supervision (Radford, A, et al., 2019).

In June 2020, GPT-3 made a significant advancement. A whopping 175 billion parameters were used to train this model. Due to its sophisticated text-generation skills, it is now widely used for a broad range of tasks, including producing emails, essays, poetry, and even computer code. It also displayed the capacity to translate across languages and respond to factual queries (Haleem, A., Javaid, M., & Singh, R. P., 2022).

When GPT-3 was introduced, it was a turning point when the world began to recognize this ground-breaking technology. Even though the models had been around for a while, it was not until GPT-3 that users had the chance to engage with ChatGPT personally, pose queries, and receive detailed and helpful answers (Chatterjee, S., & Bhattacharjee, K. K., 2020). It became obvious how influential this technology would become when individuals were able to communicate directly with the LLM in this way. GPT-3 have the capacity to generalize across a variety of linguistic tasks, making them extremely adaptable and effective for learners (Brown, T. B., et al., 2020).

The most recent version, GPT-4, maintains this pattern of exponential growth and includes the following modifications: Increased factual accuracy; a lower probability of producing unpleasant or dangerous outcomes; Improved model alignment; having the capacity to follow user motive; Improved steerability (Huang, C. H., 2021); The capacity to modify behaviour in response to user requests; internet access; The most recent upgrade offers the power to search online in real-time.

With each step forward, we go closer to a day when AI will be an integral part of our daily life, boosting our communication, creativity, and productivity. Chatbot has raised the bar for artificial intelligence and demonstrated that robots can actually "learn" the nuances of human communication and engagement (Clark, R. E., 2010).

On November 30, 2022, OpenAI made a preliminary demo of ChatGPT available online. As people disclosed instances of what the chatbot is capable of, the chatbot soon gained popularity online. Travel planning, fable writing, programming, etc. were all topics covered in the stories and examples. The chatbot gained over a million users in only five days (Madan, R., & Ashok, M., 2022).

With the use of ChatGPT, intelligent educational applications that can offer learners individualized support have been developed. The biggest worry is that students would use the model to write essays and other assignments. Universities and anti-cheating software providers are currently engaged in a cat-and-mouse game to create solutions to stop this (Bulger, M. E., & Mayer, R. E., 2019).

As of July 1st, 2023, this popular AI chatbot has more than 100 million users worldwide, placing it at the top of user-facing AI programs ever since its release. Such adoption is rare, as the chatbot was the first publicly accessible AI tool that drew people's attention and captured their imaginations as it introduced new features and capabilities. Despite impending competition from systems like Google Bard, Microsoft's AI-powered Bing, and Anthropic's Claude 2, this is still leading (Singh Gill, S., et al., 2023).

AI in Education Sector

AI can make it possible for educational organizations to gather and investigate enormous volumes of data about learning outcomes, choices, and behaviors. With the use of this data-driven methodology, educators may better understand the learning styles of their students, spot their areas of weakness and design focused remedies (Dicheva, D., Dichev, C., Agre, G., & Angelova, G., 2015). Analytics-driven by AI may help teachers make decisions based on the best available data, improve their teaching methods, and enhance the general efficacy and level of their learning. Technologies based on artificial intelligence (AI) can make it easier to develop intelligent learning materials and platforms that meet the demands of a wide range of learners (Hwang, H., Malhotra, N. K., Kim, Y., Tomiuk, M. A., & Hong, S., 2010). Based on student skills, choices, and outcomes, adaptive educational platforms incorporating AI algorithms may continuously design lessons, tests, and activities. These personalized learning experiences can help students learn more quickly, retain information, and have a greater understanding of what they are learning (Lu, J., Yao, J. E., & Yu, C., 2005). They also have the possibility of increase student engagement. Utilizing AI technology may improve learning outcomes, allow for data-driven choices, and offer individualized learning opportunities. By addressing both specific student requirements and increasing access to high-quality education, AI is being used in education (Mhlanga, D., 2021).

Artificial interactive educators with the ability to provide individualized and adaptive training have the capability to change online learning (Woolf, B. P., 2010). Artificial intelligence (AI)-based learning systems are useful instruments in the education sector because they can deliver individualized and flexible training (VanLehn, K., 2011). Careful evaluation of cognitive and motivational elements, as well as controlling prospective barriers and ethical issues, are necessary for the effective implementation of AI into education (Bulger, M. E., et al., 2019).

The adoption of artificial intelligence in the higher education sector is assessed with the help of intention to use AI and actual uses of AI measures. Intention to use AI define how frequently a user is making up his or her mind to use AI for their academic work whereas the Actual uses of AI measures will provide knowledge about how a user taking the help of AI in their academic work (Pallathadka, H., et al., 2022).

Knox, (2020) analyses the political economics of education and artificial intelligence (AI) in

China through a review of public and commercial sector initiative. There has been comparatively little research done on the topic, according to an analysis of recent literature. To bridge this gap Owoc et al., (2021), describe the advantages and difficulties of adopting artificial intelligence into the educational system, followed by a brief description of the fundamental ideas behind AI and its historical development. With the use of AI, expert systems may be created to interact with the outside world using abilities like voice recognition, visual perception, and intellectual conduct, which Sharma et al., (2021) can be found to be intrinsically human. In order to improve learning and life outcomes for everyone, Sharma et. al., (2021) aims to discuss the role of artificial intelligence in the field of education, including its market size, the effect of AI in education, and case studies regarding the present AI presence in educational institutions (smart content, smart tutoring systems, virtual instructors, and educational environments, etc.). Mijwil et al., (2022) give a summary of the importance of artificial intelligence applications, their function in learning, and potential future uses. Hemachandran et al., (2022) seek to close the gap between human and automated instructors.

Objective of the study

1. To identify the major factors which have an impact on the adoption of artificial intelligence like Chat GPT in the Higher education system in India.

2. To identify the factors influencing the adoption of artificial intelligence like Chat GPT in the Higher education system in India.

Identification of major factors influencing the use of Artificial Intelligence in the education sector

Several variables influence the use of AI in education. Artificial intelligence (AI) is becoming increasingly practical and useful in educational settings thanks to technological developments in areas like computer learning and natural language processing (Rana, P., Gupta, L. R., Kumar, G., & Dubey, M. K., 2021). Educators are drawn to AI's capacity to offer individualized educational activities based on distinct requirements and learning preferences. AI is essential for fostering openness and accessibility in education and helping learners with all kinds of learning requirements. Government initiatives and financial support may encourage the use of AI in teaching. To win over society, ethical issues relating to privacy and security of data must be resolved. Successful implementation requires adequate preparation for educators and training. Cultural perspectives on artificial intelligence and technology have an influence on adoption (Smith, J., & Johnson, A., 2020).

For the purpose of this study, the authors reviewed several other research papers to gather the crucial elements related to artificial intelligence. A comprehensive analysis of the literature provides the author with a number of significant benefits that are directly related to the application of artificial intelligence in the field of education (Srivastava, P., Hassija, T., & Goyal, A. P., 2020). The following factors were identified.

Hedonic factors

Hedonic factors are those components of consumer behavior that pertain to the sensory, fantasy, and emotional (for instance, amusement) aspects of one's come across with products/stores. The latest research has identified hedonic elements that evoke sensations of excitement, joy, and pleasure as being appealing, lovely, and mental representations. In this study, the hedonic factors have been measured by two measures i.e., Perceived Enjoyment and Perceived Satisfaction (Banik, S., & Gao, Y., 2023).

Perceived enjoyment

According to Lin et al. (2005), perceived enjoyment stands out as a key factor in users' decision to keep using web-based services. According to Davis, Bagozzi, and Warshaw (1992), perceived enjoyment is the degree to which the process of utilizing the system is judged to be pleasurable on its own merits. Everyone is intrinsically driven to keep using a service if they "feel good" while using it

(Lin, Wu, & Tsai, 2005). When it comes to user acceptability and adoption of AI apps, enjoyment is essential. According to various studies, people are more inclined to utilize AI technologies, feel satisfied after interacting with them, and even show a higher eagerness to explore and play with these technologies when they believe that such technologies are enjoyable (Wong, K. K. K., 2013). It will have substantial implications for society since it promotes the adoption and usage of AI technology on a large scale, which will raise the level of productivity, effectiveness, and overall standard of life for people (J.C. Lin, et al., 2023).

Perceived Satisfaction

According to studies, people who use AI systems claim to be more satisfied when the systems are made to properly match their requirements and aspirations (Johnson, L., et al., 2016). Users have given artificial intelligence's ability to offer personalized advice, support choice-making, and automate tasks a favorable evaluation, which has raised user satisfaction levels. Various study shows how AI might increase customer satisfaction and boost all-around public efficiency and productivity, which has important societal significance (Johnson, R., & Williams, B., 2019). Technology effectiveness, accessibility, dependability, and transparency are all significant determinants of perceived AI satisfaction. Users want systems that are easy to use, trustworthy, and that give clear justifications for any suggestions or actions in addition to expecting AI systems to offer accurate and pertinent findings. For AI systems to be widely used and accepted in a variety of industries, including healthcare, banking, transportation, and entertainment, a high degree of user happiness is essential (Owoc, M. L., Sawicka, A., & Weichbroth, P., 2019).

Convenience and Efficiency

Students may benefit from quick and simple access to resources, assistance, and knowledge thanks to AI-powered solutions. AI is attractive for jobs like research, recording information, and learning because of features like quick replies, tailored recommendations, and Continuous accessibility.

These technologies make use of artificial intelligence to give individualized learning opportunities, adjust to user preferences, and deliver quick feedback. According to the latest research, these developments can considerably help students by giving them access to a more interesting, adaptable, and accepting educational atmosphere (Clark, D. B., & Martinez-Garza, M., 2019 & Smith, J., & Johnson, A., 2018 & Johnson, R., & Williams, B., 2019).

Personalization and Adaptability

With the use of AI, learning experiences and information can be customized for each learner. AI algorithms are used by adaptive learning systems to monitor pupil progress and offer personalized educational resources, adaptive exams, and customized feedback (Lee, S., & Kim, H., 2017). The knowledge and retention of educational materials by students can be improved via personalization. These systems use artificial intelligence (AI) algorithms to assess student achievement data, pinpoint where students have weaknesses, and offer individualized study programs and feedback. It has been discovered that the adoption of adaptive learning platforms improves student engagement, motivation, and general academic achievement. By spotting misunderstandings or knowledge gaps and giving prompt remedial feedback, adaptive learning systems can promote deeper comprehension and lower the likelihood of reoccurring mistakes (Wang, M., & Han, X., 2018 & Clark, R. E., 2010).

Enhanced Learning Experience:

Chatbots and other artificial intelligence (AI) tools may replicate lively debates to provide fun and immersive learning environments. Applications for virtual reality (VR) and augmented reality (AR) that use AI can give students interactive experiences, simulations, and visualizations to help them understand and remember difficult subjects. AI in the classroom can help students develop their learning styles and critical thinking abilities (Madan, R., & Ashok, M., 2022). Virtual assistants may also provide rapid feedback and support, allowing students to get advice and help when they need it. Virtual assistants and VR/AR apps, two examples of AI technology, have enormous potential to provide students with participating and realistic learning experiences. The use of these innovations in education has the possibility of helping improve inclusiveness, individualized learning, and the acquisition of vital skills that will be required in the future (Huang, Y., Liu, D., & Cui, G., 2020 & Lee, S., & Kim, H., 2017).

Access to Diverse Resources

Platforms driven by AI can compile and filter an enormous amount of educational content from many sources, giving students a variety of resources for their research requirements. On the basis of students' interests and preferred methods of acquiring knowledge, AI algorithms may also suggest pertinent studies, papers, clips, and online programs. By giving students access to a wide range of educational resources and tools from multiple sources, these online platforms have the capacity to change higher education (Melchor, M.Q., Julián, C.P., 2008). By enabling learners to explore a wider variety of educational content and improving their overall educational experience, this improved access promotes equality and unity. AI-powered technologies have the capacity to transform the educational setting by supporting tailored instruction, enhancing lifelong learning abilities, and increasing access to a variety of resources. similarly, Additional study is required to explore long-term impacts, address biases and ethical issues, and develop effective integration remedies (Lee, S., & Kim, H., 2017 & Brown, L., & Davis, M., 2018).

Collaboration and Communication

By allowing learners to interact and collaborate electronically, AI systems encourage learning through collaboration. In addition to supporting group projects, enabling collaboration in real-time, and offering resources for sharing files, revision management, and online conversations, AI-based platforms can also improve student interaction and teamwork (Mollick, E., & Tornatzky, L. G., 2020). These instruments have the power to break down geographical barriers and unite scholars from different economic strata, promoting collaboration and strengthening the educational process. Along with educating students for the digital era, this method encourages independent thinking, creativity, and problem- solving skills. AI solutions that enable remote access and shared learning have the potential to transform the education sector by removing geographical barriers, encouraging active involvement and interaction, and allowing students to take control of their own educational experience (Dillenbourg, P., et al., 2009).

Time Management and Productivity

AI can help students be more productive and effectively manage their time. Learners may arrange their calendars, establish objectives, and monitor their progress with the use of AI-powered task administration instruments, calendar applications, and study guides (Owoc, M. L., Sawicka, A., & Weichbroth, P., 2019). AI may also generate customized schedules for studying and analyzing objective assessments, among various other prevalent jobs. In addition to offering structure and discipline to students' academic life, these instruments also aid in the development of essential skills like setting objectives, time management, and task prioritizing. Students may develop a feeling of accountability, self-determination, and self-awareness by using these resources, which will improve their capacity to properly manage their time both during their academic activities and in their future career undertakings (Lee, S., & Kim, H., 2017 & Smith, J., & Johnson, A., 2020).

Accessibility and Inclusivity

Students with disabilities or special learning requirements may find education to be more accessible with the advent of AI technology. AI solutions like text-to-speech and speech-to-text can help learners who have hearing or visual disabilities. Additionally, AI may facilitate language translation, allowing students to access course materials in the language of their choice (Pillai, R., & Sivathanu, B., 2020).

Analytical Insights and Performance Tracking

Students can gain knowledge about their performance and learning development thanks to AI-based analytics. With the use of learning analytics tools, students may discover areas for development and modify their learning tactics by analyzing data on their approach to learning, participation, and evaluation performance (Radford, A. et al., 2019). Traditional methods of evaluation frequently fall short of capturing the many facets that learners bring to learning, like their capacity for finding solutions or their ability for critical thinking. However, educators may collect real-time data on students' learning methods, metacognitive awareness, and data processing skills with the help of AI algorithms. This not only makes it possible to evaluate student performance more accurately, but it also gives students access to individualized insights that may help them plan for future educational techniques and enhance their overall learning results (Garcia, M., & Lee, S., 2017 & Johnson, R., & Williams, B., 2019).

Career and Skill Development

Based on curiosity among learners and goals, AI systems may provide personalized career guidance, employment referrals, and skill development instruments. AI-driven systems for career evaluation can offer information on viable career choices and the abilities needed, assisting learners in making well-informed decisions about their academic and professional trajectories (Sharma, U., Tomar, P., Bhardwaj, H., & Sakalle, A., 2021). These AI platforms have the potential to close the gap between school and work by revolutionizing the way individuals manage their educational and professional routes. These platforms may give personalized counseling, identify appropriate employment prospects, and offer resources to help foster the skills required for a successful professional life by utilizing artificial intelligence techniques and large volumes of knowledge (Siemens, G., & Gasevic, D., 2012). By solving the present difficulties that learners face while making career-related decisions, AI platforms can benefit society (Mollick, E., & Tornatzky, L. G., 2020 & Hirschi, A., & Herrmann, A., 2020).

Gamification and Motivation

With the help of AI, educators may encourage learners and improve learning experiences by incorporating gamified components like badges, leaderboards, and progress monitoring. In accordance with individual performance, AI algorithms may modify the level of complexity of learning activities, guaranteeing a suitable level of challenge and preserving student engagement (Smith, J., & Johnson, A., 2018). Traditional teaching approaches are frequently monotonous and unappealing to many learners, which lowers motivation and yields little outcomes for learning. AI may be used by educators to incorporate gamified features, resulting in a more interesting and engaging learning environment that ultimately increases student motivation and satisfaction (Smith, J., & Johnson, A., 2020). Education professionals may have a favourable effect on students' academic accomplishment and long-term success by enhancing learning experiences (Mekler, E. D., et al., 2017 & Dicheva, D., et al., 2015).

Table 1 shows the various factors and relevant questions asked from the respondents, as well as the references or sources used to identify the factors.

Table 1 – Questionnaire items and references

Factors	**Questions**	**References**
Adoption of AI (Intention to Use & Actual Usage)	1. I intend to use the AI chatbot frequently in the future.	Pillai, R., & Sivathanu, B. (2020)
	2. I would recommend the AI chatbot to others based on my positive experience.	
	3. Given the choice, I prefer using the AI chatbot over alternative methods for assistance.	
	4. I see myself using the AI chatbot as a regular part of my routine or workflow.	
	5. The AI chatbot has become an essential tool for me due to the enjoyment it provides.	
	6. I have actively used the AI chatbot to seek assistance or information.	
	7. The AI chatbot has been a valuable resource in solving my queries or problems.	
	8. I rely on the AI chatbot for quick and efficient responses to my inquiries.	
	9. I have found the AI chatbot to be a useful and reliable tool in my interactions.	
	10. The AI chatbot has positively contributed to my overall user experience.	Kujala, S., Roto, V., Väänänen-Vainio-Mattila, K., & Sinnelä, A. (2011)
Hedonic factors (Perceived Enjoyment)	1. Interacting with the AI chatbot is enjoyable.	
	2. I find the AI chatbot's responses to be engaging and interesting.	
	3. Using the AI chatbot is a pleasant experience.	
	4. I feel a sense of enjoyment when using the AI chatbot.	
	5. The AI chatbot provides me with entertainment while assisting me.	
	6. The AI chatbot meets my expectations in terms of providing assistance.	
	7. I am satisfied with the quality of responses and information provided by the AI chatbot.	
	8. The AI chatbot understands my needs and provides relevant and helpful solutions.	
	9. Using the AI chatbot enhances my overall satisfaction with the service or product it supports.	
	10. I am pleased with the overall performance and capabilities of the AI chatbot.	
Convenience and Efficiency	1. AI-powered tools provide me with convenient ways to access information, resources, and support.	Duan, Y., Li, H., Whinston, A. B., & Zhang, X. (2009)
	2. Instant responses, personalized recommendations, and 24/7 availability make AI appealing for my study tasks.	
	3. AI tools have improved the efficiency of my research, note-taking, and studying.	
Personalization and Adaptability	1. AI has tailored content and learning experiences to my individual needs.	Brusilovsky, P., & Peylo, C. (2003)
	2. Adaptive learning platforms powered by AI have enhanced my understanding and retention of the study material.	
	3. The personalized feedback and adaptive assessments provided by AI have been beneficial for my learning.	
Enhanced Learning Experience	1. AI technologies like virtual assistants and chatbots have created engaging and immersive learning experiences for me.	Johnson, L., Adams Becker, S., Cummins, M., Estrada, V., Freeman, A., & Hall, C. (2016)
	2. VR and AR applications powered by AI have made complex concepts more accessible and memorable for me.	
	3. I find AI-powered interactive conversations and simulations to be helpful in my learning.	
Access to Diverse Resources	1. AI-powered platforms have provided me with a wide range of educational resources from various sources.	Cho, V., & Lai, Y. (2018)
	2. The recommendations provided by AI algorithms have helped me discover relevant articles, research papers, videos, and online courses.	
	3. AI has enhanced my access to diverse resources for my study needs.	
Collaboration and Communication	1. AI tools have facilitated collaborative learning and enabled me to connect and work together with others remotely.	Holzinger, A., Nischelwitzer, A., & Meisenberger, M. (2005)
	2. AI-based platforms have supported group projects, real-time collaboration, and online discussions among students.	
	3. The collaboration features provided by AI tools have enhanced my teamwork and communication skills.	
Time Management and Productivity	1. AI has assisted me in managing my time effectively and improving my productivity.	Junco, R., Heiberger, G., & Loken, E. (2011)
	2. AI-powered task management tools, calendar integrations, and study planners have helped me organize my schedule and set goals.	

	3. Automation through AI has saved me time on routine tasks and allowed me to focus on more important aspects of my studies.	
Accessibility and Inclusivity	1. AI technologies have made education more accessible to students with disabilities or specific learning needs.	O'Brien, H. L., & Toms, E. G. (2008)
	2. Text-to-speech and speech-to-text AI tools have assisted me in accessing educational content despite visual or hearing impairments.	
	3. AI language translation support has enabled me to access educational content in my preferred language.	
Analytical Insights and Performance Tracking	1. AI-based analytics have provided me with valuable insights into my learning progress and performance.	Siemens, G., & Gasevic, D. (2012)
	2. Learning analytics tools have helped me identify areas for improvement and adjust my learning strategies.	
	3. AI has been beneficial in tracking my engagement, study habits, and assessment results.	
Career and Skill Development	1. AI platforms have offered me personalized career guidance, job recommendations, and skill development resources.	Atlas, S. (2023)
	2. AI-powered career assessment tools have provided me with insights into suitable career paths and required skills.	
	3. AI has helped me make informed decisions about my educational and professional journey.	
Gamification and Motivation	1. Incorporating gamified elements through AI has motivated me and made learning more enjoyable.	Dicheva, D., Dichev, C., Agre, G., & Angelova, G. (2015)
	2. I have remained interested in learning due to AI algorithms that adjust the level of difficulty of learning exercises based on how I perform.	
	3. I find the gamification features provided by AI to be helpful in maintaining my motivation for learning.	

The hypothesis of the study

1. The hedonic factor positively affects the Adoption of AI in the Higher Education Sector in India.

2. Convenience & Efficiency of accessing information, resources, and support positively affects the Adoption of AI in the Higher Education Sector in India.

3. Personalization & Adaptability features of AI positively affect the Adoption of AI in the Higher Education Sector in India.

4. Enhanced Learning Experiences such as virtual assistants and VR/AR applications, create engaging and immersive learning experiences for students positively affecting the Adoption of AI in the Higher Education Sector in India.

5. Access to Diverse Resources positively affects the Adoption of AI in the Higher Education Sector in India.

6. Collaboration & Communication features of AI positively affect the Adoption of AI in the Higher Education Sector in India.

7. Time Management & Productivity measures positively affect the Adoption of AI in the Higher Education Sector in India.

8. Accessibility & Inclusivity to education for students positively affects the Adoption of AI in the Higher Education Sector in India.

9. Analytical Insights & Performance tracking tools positively affect the Adoption of AI in the Higher Education Sector in India.

10. Career & Skill Development resources positively affect the Adoption of AI in the Higher Education Sector in India.

11. Incorporating Gamification & Motivation in AI positively affects the Adoption of AI in the Higher Education Sector in India.

Research Methodology

Data Collection and Analysis Method

This study collects the data with the help of a research questionnaire. This research questionnaire uses Likert's 5-point scale, with options including "strongly disagree", "disagree", "normal", "agree", and "strongly agree". The questionnaire was issued and collected a hundred responses from eminent scholars affiliated with the education sector. The technique of partial least squares structural equation modeling (PLS-SEM) is used in Smart-PLS 4.0 to create a reflective measurement model that measures the correlation between observational data and latent variables. The process for finding or creating predictive models is partial least squares structural equation modeling (PLS-SEM). It is superior to the general linear structural relationship framework, which is ideal for exploratory research, particularly for the causality model evaluation between latent variables (Pavlou, P.A.; Fygenson, M., 2006 & Melchor, M.Q.; Julián, C.P., 2008).

The PLS-SEM technique was developed as a prediction-oriented approach to SEM that relaxes the requirements for data and relationship definition established by CB-SEM (Hair Jr., J.F., et al., 2014).

When the following circumstances occur, PLS-SEM becomes a good substitute for CB-SEM (Bacon, L. D., 1999 & Wong, K. K., 2010).

1. A small sample size.
2. The existing theory for applications is limited.
3. Accurate prediction is crucial.
4. It is impossible to guarantee accurate model specifications.

The primary goal of PLS-SEM is to identify causal relationships that have statistically significant reciprocal linear relationships. The creation of theoretical models is a good fit for it. PLS-SEM is a technique used in this study to investigate the connection between the research variables. The study comprises eleven factors to be tested using the PLS-SEM technique (Wang, M., & Han, X., 2018). The sample size used in this study is a hundred. To obtain path coefficients and significance, the repeated sampling is carried out 5000 times using the PLS Algorithm and Bootstrapping. For the analysis purpose, Smart PLS 4.0 is used. The primary data used in the study was obtained through a questionnaire. Based on an extensive review of the literature, the questionnaire's variables were developed. The Google Forms survey received 100 responses in total. In this study, the researcher collected data using a convenient simple non-random sampling technique since the respondents were affiliated with educational institutions (Henseler, J.; Chin, W.W., 2010).

Analysis of the study

Background variable analysis

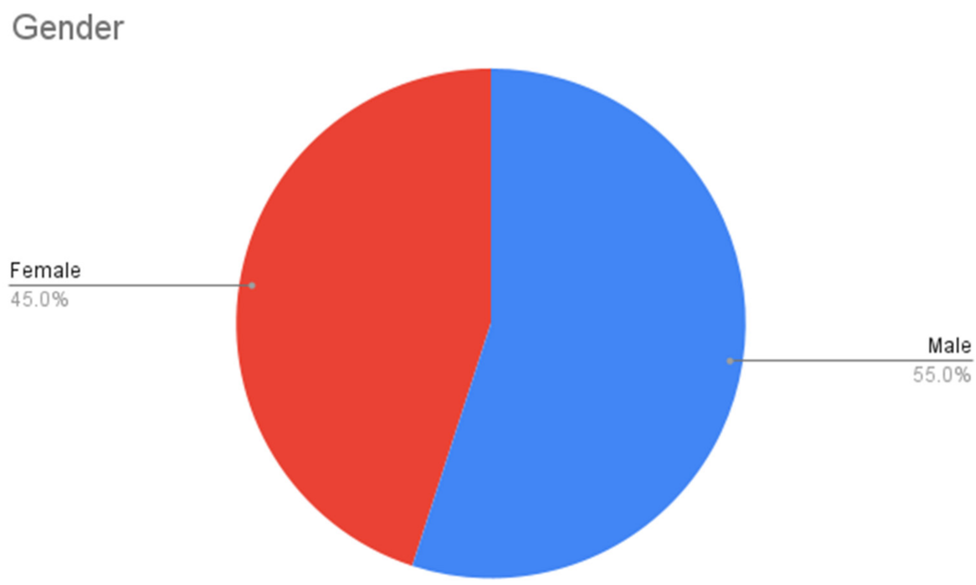


Figure 1 – Gender

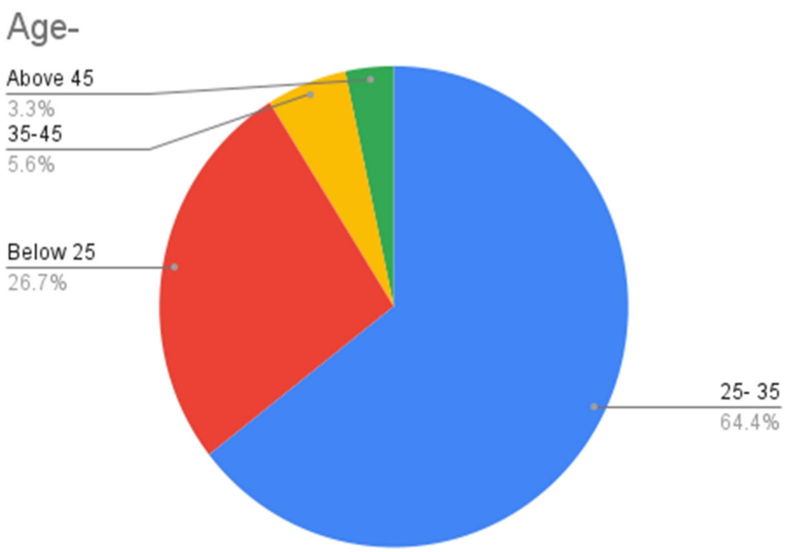
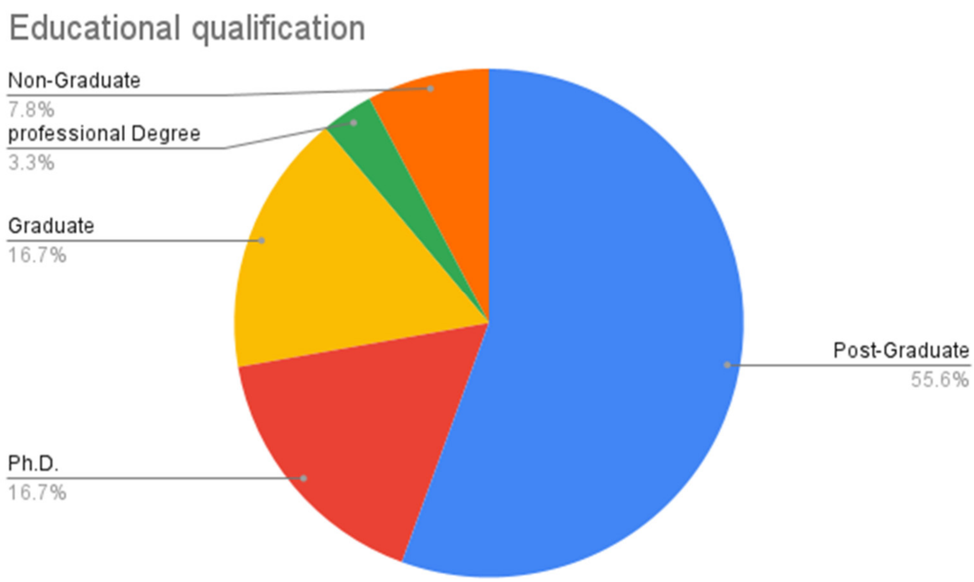


Figure 2 – Age



Source: data compiled through Google forms

Figure 3 – Education Level

The collected data were analysed, and the author discovered that there were 45 percent female and 55 percent male among the respondents, indicating that we balanced respondents concerning gender. In addition, the majority of respondents were in the 25 to 35 age range, and the majority were post-graduates, indicating that the majority of users were associated with higher education. As a result, our analysis will produce more accurate results since the study's primary objective is to assess the impact of artificial intelligence on higher education.

Reliability and Validity Test

In order to conclude the analysis of the structural model, just as with any other marketing research, it is crucial to establish the validity and reliability of the latent variables. Concepts like validity and reliability are used to assess the standard of research. They demonstrate how effectively a methodology, method, or test examines anything. Validity is concerned with a measure's correctness, whereas reliability is concerned with its consistency choice (Woolf, B. P., 2010)

Particularly in quantitative research, reliability, and validity should be taken into account while developing the research design, selecting your method of inquiry, and summarizing results.

Latent variable composition reliability (CR) & Cronbach's alpha are used to assess internal consistency. The required value must be higher than 0.7. In order to determine the connection between items that comprise the same scale and to identify the average variance extraction (AVE), convergent validity is mostly used. The AVE value should be higher than 0.5. The square root value of the AVE is used to examine the discriminant validity, which measures the association between items with various aspects. Discriminative validity is demonstrated if the diagonal AVE's square root value exceeds the horizontal or vertical column's correlation coefficient value (Bagozzi, R.P.; Yi, Y., 1988 & Fornell, C.; Larcker, D.F., 1981).

Table 2 – Measurement model parameter estimation

Dimensions	Question Items	Factor Loading	Cronbach's α	CR	AVE
Adoption of AI	AAI 1	0.810	0.924	0.929	0.596
	AAI 2	0.783			
	AAI 3	0.754			
	AAI 4	0.684			
	AAI 5	0.712			
	AAI 6	0.712			
	AAI 7	0.859			
	AAI 8	0.808			
	AAI 9	0.772			
	AAI 10	0.811			
Hedonic factors	HED 1	0.817	0.916	0.924	0.579
	HED 2	0.822			
	HED 3	0.833			
	HED 4	0.629			
	HED 5	0.476			
	HED 6	0.836			
	HED 7	0.808			
	HED 8	0.690			
	HED 9	0.810			
	HED 10	0.803			
Convenience & Efficiency	CE 1	0.910	0.855	0.857	0.776
	CE 2	0.843			
	CE 3	0.888			
Personalization & Adaptability	PA 1	0.806	0.837	0.871	0.752
	PA 2	0.873			
	PA 3	0.918			
Enhanced Learning Experience	ELE 1	0.866	0.854	0.869	0.773
	ELE 2	0.846			
	ELE 3	0.924			
Access to Diverse Resources	ADR 1	0.813	0.854	0.864	0.776
	ADR 2	0.893			
	ADR 3	0.934			
Collaboration & Communication	CC 1	0.921	0.892	0.935	0.819
	CC 2	0.878			
	CC 3	0.916			
Time Management & Productivity	TMP 1	0.915	0.896	0.898	0.829
	TMP 2	0.882			
	TMP 3	0.933			

Accessibility & Inclusivity	AI 1	0.862	0.844	0.852	0.761
	AI 2	0.849			
	AI 3	0.906			
Analytical Insights & Performance Tracking	AIPT 1	0.860	0.843	0.854	0.760
	AIPT 2	0.855			
	AIPT 3	0.900			
Career & Skill Development	CSD 1	0.908	0.902	0.924	0.835
	CSD 2	0.895			
	CSD 3	0.937			
Gamification & Motivation	GM 1	0.895	0.886	0.887	0.815
	GM 2	0.893			
	GM 3	0.920			

Source: data complied through Smart PLS 4.0

Table 2 reflects the various dimensions, factor loading Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

The dimension "Adoption of AI" consists of 10 question items (AAI 1 to AAI 10). The factor loadings for the question items range from 0.684 to 0.859, indicating that these items are strongly related to the underlying construct of "Adoption of AI." The high Cronbach's alpha (0.924) and Composite Reliability (0.929) values suggest good internal consistency and reliability of the items within this dimension. However, the Average Variance Extracted (AVE) is 0.596, which is slightly below the commonly accepted threshold of 0.7 for AVE, indicating that there might be some shared variance among the items but also some variance due to measurement error.

The hedonic factors dimension represents factors related to pleasure and enjoyment derived from AI adoption. It consists of 10 question items (HED 1 to HED 10). Most of the question items have high factor loadings (ranging from 0.476 to 0.836), indicating strong associations with the underlying construct. The Cronbach's alpha (0.916) and Composite Reliability (0.924) values suggest good internal consistency and reliability, while the AVE is 0.579, indicating acceptable convergent validity.

The convenience & Efficiency (CE) dimension represents factors related to the convenience and efficiency of AI adoption. It consists of three question items (CE 1 to CE 3). All three question items have relatively high factor loadings (ranging from 0.843 to 0.910), indicating strong associations with the dimension. The Cronbach's alpha (0.855) and Composite Reliability (0.857) values suggest good internal consistency and reliability, while the AVE is 0.776, indicating acceptable convergent validity.

Personalization & Adaptability (PA) dimension represents factors related to personalization and adaptability in the context of AI adoption. It consists of three question items (PA 1 to PA 3). All three question items have relatively high factor loadings (ranging from 0.806 to 0.918), indicating strong associations with the dimension. The Cronbach's alpha (0.837) and Composite Reliability (0.871) values suggest good internal consistency and reliability, while the AVE is 0.752, indicating acceptable convergent validity.

The enhanced Learning Experience (ELE) factor represents the impact of AI adoption on the learning experience. It includes aspects related to how AI technologies enhance learning outcomes and make the learning process more effective and engaging. The three question items (ELE 1 to ELE 3) have relatively high factor loadings (ranging from 0.846 to 0.924), indicating strong associations with this dimension. The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.854 and a Composite Reliability of 0.869. The AVE value of 0.773 indicates acceptable convergent validity. This factor highlights the potential benefits of AI in educational settings, where AI can support personalized learning and improve the overall learning experience.

The access to Diverse Resources (ADR) factor represents the extent to which AI adoption provides access to diverse resources and information. It includes aspects related to how AI technologies enable users to access a wide range of resources and knowledge. The three question items (ADR

1 to ADR 3) have relatively high factor loadings (ranging from 0.813 to 0.934), indicating strong associations with this dimension. The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.854 and a Composite Reliability of 0.864. The AVE value of 0.776 indicates acceptable convergent validity. This factor highlights the role of AI in expanding access to information and resources, contributing to more informed decision-making and problem-solving.

The collaboration & Communication (CC) factor represents the impact of AI adoption on collaboration and communication. It includes aspects related to how AI technologies facilitate collaboration among individuals and teams and improve communication channels. The three question items (CC 1 to CC 3) have relatively high factor loadings (ranging from 0.878 to 0.921), indicating strong associations with this dimension. The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.892 and a Composite Reliability of 0.935. The AVE value of 0.819 indicates acceptable convergent validity. This factor emphasizes the potential of AI to enhance teamwork and communication in various settings.

Time Management & Productivity (TMP) factor represents the impact of AI adoption on time management and productivity. It includes aspects related to how AI technologies help users manage their time more effectively and improve overall productivity. The three question items (TMP 1 to TMP 3) have relatively high factor loadings (ranging from 0.882 to 0.933), indicating strong associations with this dimension. The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.896 and a Composite Reliability of 0.898. The AVE value of 0.829 indicates acceptable convergent validity. This factor highlights the potential of AI to optimize tasks, streamline workflows, and save time.

The accessibility & Inclusivity (AI) factor represents the extent to which AI adoption promotes accessibility and inclusivity. It includes aspects related to how AI technologies make services and resources more accessible to diverse populations, including individuals with disabilities. The three question items (AI 1 to AI 3) have relatively high factor loadings (ranging from 0.849 to 0.906), indicating strong associations with this dimension. The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.844 and a Composite Reliability of 0.852. The AVE value of 0.761 indicates acceptable convergent validity. This factor underscores the potential of AI to break down barriers and create more inclusive environments.

The analytical Insights & Performance Tracking (AIPT) factor represents the impact of AI adoption on providing analytical insights and performance tracking capabilities. It includes aspects related to how AI technologies enable users to gain valuable insights from data and track performance metrics effectively. The three question items (AIPT 1 to AIPT 3) have relatively high factor loadings (ranging from 0.855 to 0.900), indicating strong associations with this dimension. The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.843 and a Composite Reliability of 0.854. The AVE value of 0.760 indicates acceptable convergent validity. This factor emphasizes the potential of AI to enhance decision-making and performance evaluation through data analytics and tracking tools.

Career & Skill Development (CSD) factor represents the impact of AI adoption on career growth and skill development. It includes aspects related to how AI technologies contribute to professional development and acquiring new skills. The three question items (CSD 1 to CSD 3) have relatively high factor loadings (ranging from 0.895 to 0.937), indicating strong associations with this dimension. The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.902 and a Composite Reliability of 0.924. The AVE value of 0.835 indicates acceptable convergent validity. This factor highlights the potential of AI to empower individuals with new skills and opportunities for career advancement.

Gamification & Motivation (GM) factor represents the impact of AI adoption on gamification and motivation. It includes aspects related to how AI technologies leverage gamification techniques to motivate users and enhance engagement. The three question items (GM 1 to GM 3) have relatively high factor loadings (ranging from 0.893 to 0.920), indicating strong associations with this dimension.

The dimension demonstrates good internal consistency and reliability, with a Cronbach's alpha of 0.886 and a Composite Reliability of 0.887. The AVE value of 0.815 indicates acceptable convergent validity. This factor highlights the potential of AI to create more engaging and motivating experiences, particularly in educational and training contexts.

Table 3 – Discriminant validity test (Fornell–Larcker)

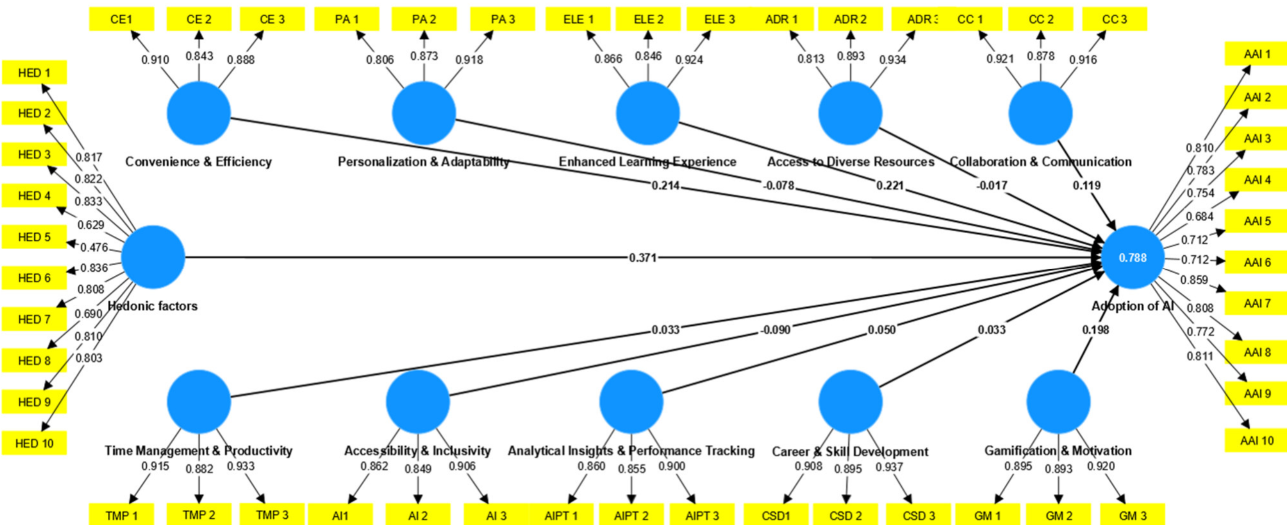
Dimensions	AVE	Square root value of AVE
Adoption of AI	0.596	0.772
Hedonic factors	0.579	0.761
Convenience and Efficiency	0.776	0.881
Personalization & Adaptability	0.752	0.867
Enhanced Learning Experience	0.773	0.879
Access to Diverse Resources	0.776	0.881
Collaboration & Communication	0.819	0.905
Time Management & Productivity	0.829	0.910
Accessibility & Inclusivity	0.761	0.872
Analytical Insights & Performance Tracking	0.76	0.872
Career & Skill Development	0.835	0.914
Gamification and Motivation	0.815	0.903

Source: data complied through Smart PLS 4.0

Table 3 shows that the factor loadings of all the survey questions in this study aspect are higher than 0.7, which satisfies the verification criteria. All of the dimensions' Cronbach's alpha and CR values are higher than 0.7, which denotes strong internal consistency and reliability. Each dimension's AVE value exceeds 0.5, which is a sign of excellent convergent validity. Table 3 demonstrates that the diagonal AVE's square root value is higher than the matrix's other correlation coefficient values. The results in the heterotrait-monotrait analysis are all less than 0.9, which denotes high discriminant validity.

Structural Equation Modeling Analysis

Make sure to verify that the issue of collinearity has been solved before analyzing structural equation modeling. There may be a collinearity issue between the dimensions if the Variance Inflation Factor (VIF) is more than 5 (Hair, J.F.; Ringle, C.M.; 2011).



Source: Complied through Smart PLS 4.0

Figure 4 – Model of PLS-SEM path analysis diagram

Figure 4 reflects the path analysis diagram showing the impact of various factors on the Adoption of AI. There was a total of eleven factors were taken into consideration for identifying which factors have a major impact and which factors have a minor impact on the adoption of AI.

Table 4 – Model fit Table

Model fit Measures	Estimated model
SRMR	0.095
d_ULS	11.514
d_G	07.741
Chi-square	3268.954
NFI	0.506

Source: data complied through Smart PLS 4.0

There is no collinearity among the study's dimensions, according to the structural equation modeling's VIF value, which is less than 5. The most frequently employed indicators for PLS-SEM to assess the suitability of the overall model include SRMR, and NFI. The SRMR value can vary from 0 to 1. A decent fit of the model can be said to exist when the SRMR is less than 0.08. The NFI value might be between 0 and 1. The performance of NFI improves with increasing NFI value (Bentler, P.M.; Bonett, D.G. 1980 & Henseler, J.; et al., 2013).

In this study Table 4 shows that SRMR value is 0.095, which is typically considered acceptable. d_ULS is a measure of the discrepancy between the model-implied matrix and the observed matrix, computed using unweighted least squares estimation. The d_ULS value of 11.514 indicates how well the model reproduces the observed data. Smaller values of d_ULS indicate a better fit.

d_G is another measure of the discrepancy between the model-implied matrix and the observed matrix, computed using geodesic distances. Like d_ULS, lower values of d_G indicate a better fit. In this analysis, the d_G value is 7.741, suggesting a relatively good fit between the model and the data.

The Chi-square test is a traditional goodness-of-fit measure used in statistical modeling. In SEM, it assesses the discrepancy between the observed and model-implied covariance matrices. The Chi-square value reported here is 3268.954.

The NFI value reported here is 0.506, which is relatively low. NFI values range from 0 to 1, with values closer to 1 indicating a better fit.

Overall, based on the model fit measures provided, it appears that the model shows acceptable fit in some aspects (e.g., SRMR and d_G) but may have some room for improvement.

In the next section, the author performs the bootstrapping technique to obtain the result. 5000 times repeated sampling is performed using the PLS Algorithm and Bootstrapping to yield path coefficients and significance.

Table 5 – Path analysis verification Bootstrapping for 5000 sample

Path Analysis	T statistics	P values
Hedonic factors -> Adoption of AI	**3.945**	**0.000**
Analytical Insights & Performance Tracking -> Adoption of AI	0.409	0.682
Career & Skill Development -> Adoption of AI	0.393	0.695
Gamification & Motivation -> Adoption of AI	**2.195**	**0.028**
Convenience & Efficiency -> Adoption of AI	**2.603**	**0.009**
Personalization & Adaptability -> Adoption of AI	0.662	0.508
Enhanced Learning Experience -> Adoption of AI	1.867	0.062
Access to Diverse Resources -> Adoption of AI	0.232	0.817
Collaboration & Communication -> Adoption of AI	1.516	0.130
Time Management & Productivity -> Adoption of AI	0.306	0.759
Accessibility & Inclusivity -> Adoption of AI	0.776	0.438

Source: data complied through Smart PLS 4.0

The path analysis and R2 are used to examine and explain the model verification. The path analysis uses the value of t-statistics to assess the validity of the hypothesis. If the t value is more than 1.96, then the significance threshold is 0.05. When the t value is more than 2.58, it has reached a significant threshold of 0.01. When the t value is greater than 3.29, it has reached the 0.001 level of significance. In Table 5 out of the eleven factors only three factors i.e., Hedonic factors, Gamification & Motivation, and Convenience & Efficiency factors t statistics are above the standard value which means only H1, H2, and H11 are accepted and valid while other hypotheses are rejected.

Table 6 – R Square and Adjusted R Square

Measures	**Value**
R square	0.788
Adjusted r square	0.762

Source: data complied through Smart PLS 4.0

The R2 value is used to assess the model's ability for explanation. The R2 value ranges from 0 to 1. The explanatory power increases as the value increases. The model's explanatory power is considered to be moderate when the R2 value is near 0.50. The model is considered to have a high level of explanatory power when the R2 value is near 0.75. In Table 6 R square value is 0.788 and the adjusted R square is 0.762 which reflects that the explanatory power of the included factor on the adoption of Artificial intelligence is 76.20 percent. Therefore, we can say that the model used in this study has a high degree of explanatory power for the latent variables.

Conclusion of the study

The final findings of the study reveal that the overall model is fitted and has good validity and reliability as it satisfies all the related measures. The contribution of the study is that it helps the researchers to find the main factors that have an impact on the adoption of artificial intelligence in the education sector. with the help of PLS-SEM analysis we find that the adoption of Artificial Intelligence like chat GPT in India is highly influenced by hedonic factors, secondly by gamification and motivation factors and thirdly by convenience & efficiency factors as their t-statistics value is within the standard limit while other factors have very low or no influence. After analysis of the data, it became evident that Indian users' main concerns with AI adoption are about gamification, hedonic, and convenience. This does not imply that AI and other elements are unrelated. Gamification and hedonic elements provide users enjoyment and pleasure, allowing them to fully enjoy using AI. Convenience and efficiency attributes enable Indian people to utilize a growing selection of AI-associated platforms since they make using AI easier and more convenient for users. The hedonic aspects, gamification features, and convenience and efficiency measurements must therefore be carefully implemented while developing artificial intelligence-based applications for higher education in the Indian context.

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