Impact of Artificial Intelligence, Smart Learning and Belief About Future on Academic Performance & Moderating Effect of Desire for Knowledge

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Abstract

In the modern education system, using artificial intelligence and smart learning techniques has become vital for students' academic success. This research examines the direct impact of smart learning, artificial intelligence, and beliefs about the future on academic performance. It further investigates whether the desire for knowledge mediates the relationships between these variables. A structural questionnaire was designed using the existing literature, and data was collected through face-to-face distribution. The respondents have diversified demographic dimensions for which a sample of 317 was empirically tested with the help of MS-Excel and Smart PLS version 4. The results signify the following output: (1) artificial intelligence, desire for knowledge, and smart learning promote the academic performance of the study. (2) Desire for knowledge fully mediates the relationship between smart learning and academic performance and between beliefs about the future and academic performance, respectively. A comprehensive list of policy recommendations is also provided

Keywords

Artificial Intelligence, Smart Learning, Desire for Knowledge, Academic Performance, Chinese Students.

1. Introduction

Artificial intelligence (AI) and social media have recently reshaped how we live and connect with the world, making communication faster, more efficient, and personalized. While AI platforms like Chat GPT and virtual assistants, with the aid of computer algorithms, provide hands-on and interactive experiences to users (**Salas-Pilco; Yang**, 2022) social media facilitates sharing and making real-time information accessible, fostering global connections. This combination has simplified our daily lives, offering instant solutions, improving access to knowledge, and enabling more interactions across diverse communities (**Hu *et al.***, 2023). In the domain of education, these technologies provide a synergy to students to improve their problem-solving skills and academic performance. Generative tools like Chat GPT are proving powerful media in higher education to help students and educators with tasks such as answering questions, generating ideas, and simplifying complex topics (**Ray**, 2023). Therefore, AI and social media have changed how education works, and students interact with digital content and their social world (**Becker *et al.***, 2023).

Previous studies have highlighted how AI makes it easier for students to access information and participate in online communities (**Koyuturk *et al.***, 2023). However, constantly being exposed to content chosen by algorithms and the addictive nature of social media can affect student's academic performance and mental health (**Ouyang *et al.***, 2023). Previous studies showed that using Generative AI tools like Chat GPT at the university level can lead to students for better academic results (**Tlili *et al.***, 2023). By providing personalized help, feedback, and relevant information, these AI tools help students understand complex topics, improve their problem-solving skills, and enhance the overall learning experience (**Sánchez-Reina *et al.***, 2023). In addition, AI technologies are powerful tools that help students manage their time, tasks, and extra learning materials (**Whelan *et al.***, 2020).

This means that AI and social media have jointly transformed learning and students' ability to connect with others online (**Dimitriadou; Lanitis**, 2023). This transformation is significant for the younger generation, as AI and social media have become essential parts of their education and daily lives. Even though AI and social media play a vital role in students' academic performance, their mental health has not been studied thoroughly and needs more research (**Bays *et al.***, 2023). It is also necessary to study how a synergy between AI and social media can be beneficial to students and educators; and how they impact university students' academic success and mental health (**Yu; Guo**, 2023).

Although there is no dearth of studies that have looked into how AI and social media impact academic performance (**Hu *et al.***, 2023; **Whelan *et al.***, 2022; **André *et al.***, 2018); however, not much research has been carried out on the direct impact of smart learning, artificial intelligence, and beliefs about the future on academic performance and mental health , nor has been examined how the desire for knowledge affect their relationship. This study also examines how students view AI technology, such as Chat GPT, that can help in education by improving learning through experiences, assessments, and smart tutoring systems. This study is based on the premise that university life often brings anxiety, pressure and stress; however, AI has the potential to make these feelings worse or help to reduce them (**Chassignol *et al.***, 2018; **Alqahtani *et al.***, 2023). Another unique contribution of this study is to examine how Bandura's social learning theory (SLT) can be applied to understand social interactions and academic performance impacted by new AI technologies, such as Generative AI or Chat GPT. The study also measures the AI ability to customize and deliver smart learning content in accordance with SLT.

2. Theoretical Background

2.1. Social Learning Theory

Bandura's social learning theory (SLT) has provided some relevant arguments while creating a linkage between social media and related technologies like AI along with the academic performance, and the mental health (**Boahene *et al.***, 2019). According to this theory, social networks are crucial in determining the abilities of the individuals (**Alturki *et al.***, 2022). Based on this notion, studies have explained how outside factors can have a significant impact on the learning (**Yu *et al.***, 2010). The stated theory further explores the role of the mental and environmental factors in shaping the attitudes and learning habits of individuals (**Alturki *et al.***, 2022). In this view, learning is not seen as a group effect where under the condition of the collaborative age, people aim to start the overall learning phase with sharing of the knowledge (**Ali *et al.***, 2016).

Bandura's critical theory has also stated how social networks and relevant technologies like AI can significantly affect both learning and academic performance (**Jia *et al.***, 2024). Artificial intelligence has offered several personalized learning outcomes that are further being adapted through smart learning techniques (**Naser *et al.***, 2015). Smart learning fits well with the main ideas of SLT. In smart learning, students can explore different topics with SLT factors and peer influences to shape learning outcomes (**Kaliisa *et al.***, 2022). This means that students do not passively receive information but actively seek out knowledge. This matches Bandura's idea that people are capable to organize their learning in social settings (**Grover *et al.***, 2022). This refers to SLT's concept of group goal alignment which believe that learning happens together. Bandura has argued that learning is often a team effort within social groups, where shared goals can significantly impact how well perform and the results they achieve(**Yu *et al.***, 2010). The competitive element, such as feeling excited when doing better than classmates, can also be connected to SLT (**Hill *et al.***, 2009).

Moreover, the interest in using new AI technologies, such as Generative AI tools like Chat GPT (**Ma; Huo**, 2023), new social media apps fits well with SLT focus. Just as SLT recognizes that different social interactions affect learning outcomes, smart learning sees the importance of technological tools in improving academic performance (**Alamri *et al.***, 2020). These tools can expand social networks and act as personalized teaching aids that significantly affect learning outcomes and mental health. AI has the ability to customize and deliver engaging content in accordance with SLT.

Therefore, understanding how AI and social media can improve academic success and support mental well-being, it is crucial to engage in a more extensive discussion about blending of smart learning and technology in education.

2.2. Literature Review

Research studies show that AI is a powerful tool having its educational influence to improve learning and enhance academic performance (**Naser *et al.***, 2015; **Yu**, 2023). Additionally, while solving the educational challenges, it is imperative that people from different fields need to work on collaborative grounds (**Zawacki-Richter *et al.***, 2019). Research has made evident various sets of challenges linked with learning and their solution through AI (**Tsai *et al.***, 2023). Moreover, platforms like Chat GPT and other computer programs can not only create text but also images as per the need and requirements of individuals (**Ma; Huo**, 2023). They give students hands-on and interactive experiences that make it easier to understand what they are learning (**Salas-Pilco; Yang**, 2022). These technologies mimic real-world situations, helping students apply what they learn in practice and improve their problem-solving skills. In short, AI Tools like Chat GPT can positively influence students' academic performance.

Using AI effectively in education requires well-thought-out plans and privacy to ensure ethical use (**Pang**, 2024). It is important to remember that teachers and mentors are still the most essential part of the education tools; hence, AI should be used to support, not replace, human teaching (**Yu; Guo**, 2023; **Dimitriadou; Lanitis**, 2023). For example, AI creates customized learning experiences based on a student's skills and interests. This can help keep students more interested, motivated and better at understanding their learning (**Yu**, 2023). Adaptive learning tools can identify areas where students are struggling, and provide specific help to improve their understanding of important topics (**Arunachalam; Velmurugan**, 2018). AI can also create learning materials like quizzes, exercises, and study guides, making learning more interesting and useful. This not only saves teachers time but also ensures students get high-quality resources that match with their learning goals (**Zhao; Li**, 2023). By studying AI goals in education, we aim to understand how it can benefit students, enhance learning outcomes, and reshape their learning methods (**Chango *et al.***, 2021). Therefore, if students stay focused and use AI effectively, they can unlock more options to improve student learning and academic performance (**Salas-Pilco; Yang**, 2022).

Smart learning has the potential to blend digital tools like AI and social media, to transform education and learning environments (**Allal-Chérif *et al.***, 2021). This change in teaching methods is seen through personalized and engaging learning experiences supported by AI analysis (**Muro *et al.***, 2018). Smart learning environments give students unmatched access to educational resources (**Samaha; Hawi**, 2016). Educational institutions use smart learning to increase student involvement, create teamwork, support mental health and improve academic performance (**Boer *et al.***, 2021). Universities use smart learning technology to develop and welcome educational spaces that enhance students' well-being (**Embarak**, 2022). The key study found that smart learning programs positively affect students' grades and mental health. AI and social media can help create lively learning environments that motivate students (**Tomporowski *et al.***, 2008). These factors are essential for success in schools and offer good mental health to students.

AI uses data to personalize learning, giving students smarter support that can help them learn better (**Kinshuk *et al.*,** 2016). This personalized help can greatly boost students' understanding and success. Another argument to prove that AI and social media can enhance smart learning, through its various tools like Chat GPT and virtual assistants, it has been proven that active or smart learning makes it easier to share knowledge quickly, which consequently improves academic results (**Beerbaum**, 2023). When used with smart learning environments, social media can also provide emotional support and improve learning by building friendships and sharing mental health tips (**Criado; Gil-Garcia**, 2019). Smart learning makes students more curious and better at solving problems (**Lu *et al.***, 2022). People work together on smart learning projects, bringing in fresh ideas to education (**Akhrif *et al.***, 2020). When these tools are combined, they work together to improve students' learning and mental health (**Al-Marghilani**, 2022). Notably, research shows that **Martinez-Perez *et al.*** (2020) research highlights the important role of AI and smart learning in improving student academic performance.

3. Research Methods

The study utilized a quantitative research design wherein primary data was collected through a survey questionnaire. The sample comprised students from various universities in China. The eligibility criteria for sample selection were the use of the internet and knowledge of AI learning tools. the questionnaire also collected adding demographic variables like age, gender, education, usage of AI tools, and daily internet usage. The secondary data sources comprised document reviews and a critical analysis of previous research, which became the source of questionnaire items for all the variables of the study.

The variables of the study included artificial intelligence, smart learning, beliefs about the future, desire for knowledge (also known as Epistemic Curiosity), and academic performance. The measurement of artificial intelligence was based on eight items, while there were five items for smart learning, five items for beliefs about the future, four items for the desire for knowledge, and two items for academic performance. All the variables were measured on a 5-point Likert scale with strongly disagree, disagree, neutral, agree, and strongly agree as options. The given items were retrieved from previous validated studies but slightly modified to make them suitable for the current study. Table 1 presorts the variables, their measurement items and sources drawn from.

Table 1. Variables, Measurement items and Sources.

Variables	Measurement scale	Source
Artificial Intelligence (AIN)	1. ChatGPT enhances learning performance. 2. ChatGPT boosts learning efficiency. 3. ChatGPT improves learning outcomes. 4. ChatGPT fosters collaboration. 5. ChatGPT optimizes the learning process. 6. ChatGPT's multifaceted capabilities are impressive. 7. ChatGPT enriches the learning experience. 8. ChatGPT sharpens inquiry precision with targeted follow-up questions.	(**Shahzad *et al.***, 2024a)
Smart Learning (SML)	1. Smart technologies help me learn diverse topics. 2. Smart technologies encourage group learning. 3. Smart technologies improve my performance compared to others. 4. Smart technologies make learning new topics enjoyable. 5. Smart technologies make learning new applications enjoyable.	(**Zang *et al.***, 2022)
Beliefs about the future (BAF)	1. I have the confidence I need to solve future problems. 2. I have confidence that I will be a useful person in the future. 3. I expect to achieve what I want. 4. I envision a pleasant future for myself. 5. It is possible for me to find satisfaction in the future.	(**Kim; Jang**, 2015)
Epistemic Curiosity/ Desire for knowledge (DIK) (Mediating variable)	1. I enjoy exploring new ideas. 2. I enjoy learning about subjects that are unfamiliar to me. 3. I find it fascinating to learn new information. 4. I enjoy learning something new and finding out more about it.	(**Lee *et al.***, 2022)
Academic/Education performance (ACP)	1. I expect good grades in courses where ChatGPT is heavily used. 2. I expect better grades when in-class activities are replaced by ChatGPT-based activities.	(**Islam**, 2013)

The data was analyzed using descriptive statistics techniques. Initially, a demographic analysis of age, gender, education, daily internet use and use of AI tools was carried out to understand frequency distribution, percentage share, and cumulative percentage share. The descriptive results covered how the average responses were found, along with their deviation and normality trend of data. Alpha, Composite Reliability, and Average variance extracted were tabulated to check the study's outer model/measurement model. The discriminant validity of the latent variables and their items were measured using three advanced measures: HTMT ratio, Fornell-Larcker, and loadings-cross loadings. In the end, both direct and mediating analyses were conducted, and the coefficient showed the direction and strength of the independent variables on academic performance. In contrast, the mediation analysis aimed to justify whether it is partial, full, or no mediation of Desire for Knowledge.

4. Results and Discussion

4.1. Demographic Output

The sample of the study comprised 317 respondents, out of which there were 196 (61.8%) male and 121 (38.17%) female respondents. In the age category, there were 67 (21.14%) respondents in 18-21 years category; 111 (35.02%) respondents in 29-35 years category; 82 (25.87%) respondents in 29-35 years category; and 57 (17.98%) in more than 35 years category. The overall age distribution confirms that the biggest participation was from those in the age range of 22-28 years. In terms of education distribution, it was revealed that 50 (17.67%) respondents held a diploma; 100 (35.34%) respondents had a bachelor's degree; 106 (37.46%) respondents had a master's degree; and 27 (9.54%) respondents had a doctoral degree. The overall education distribution confirms the biggest participation from respondents with a master's degree. The daily internet use for academic and problem-solving purposes showed that 134 (42.27%) respondents used the internet for 1-4 hours; 167 (52.68%) used it for 4-8 hours; and 16 (5.05%) respondents used the internet for over 8 hours. The overall distribution confirms the highest participation from respondents who used the internet for 4-8 hours daily. Table 2 presents the summary of the demographic profile of respondents.

Table 2: Demographic Profile of Respondents.

Demographic Factor	Category	Frequency	Percentage (%)	Cumulative (%)
Gender	Male	196	61.83	61.83
	Female	121	38.17	100.00
Age	18-21 Years	67	21.14	21.14
	22-28 Years	111	35.02	56.15
	29-35 Years	82	25.87	82.02
	Mor than 35 Years	57	17.98	100.00
Education	Diploma	50	17.67	17.67
	Bachelor's degree	100	35.34	53.00
	Master's degree	106	37.46	90.46
	Doctoral degree	27	9.54	100.00
Daily Internet Use	1-4 hours	134	42.27	42.27
	4-8 hours	167	52.68	94.95
	More than 8 hours	16	5.05	100.00
Use of AI Tools	Information gathering	37	11.67	11.67
	Language Practice	49	15.46	27.13
	Concept Exploration	34	10.73	37.85
	Brainstorm Ideas	26	8.2	46.06
	Step-by-step Explanation	23	7.26	53.31
	Turn the Learning Materials into Quizzes	64	20.19	73.5
	Summarization of Texts	53	16.72	90.22
	Note-taking	31	9.78	100

4.2. Descriptive Results

The descriptive results comprised the mean value, observed standard deviation, excess kurtosis, and skewness. All these measures depicted both central tendency and dispersion. The measurement of Artificial Intelligence (AIN) has five items from AIN1 to AIN5. The mean scores for all five items except AIN3 are above 3 and approaching 4, representing strongly agree on the Likert Scale. It means that respondents are targeting the agreed points about the asked statement through a questionnaire. The deviation in the mean score is 1.086, whereas the excessive kurtosis and skewness are -0.63 and 0.356. For most of the skewness, the acceptable range is between -1 and +1 (**Bulmer**, 1979). Additionally, acceptable excess kurtosis values fall between -2 and +2 for many practical purposes, respectively (**West *et al.***, 1995).

The second variable of Smart Learning (SML) has four items from SML1 to SML 4. The mean scores for all four items were found as 3.665, 3.764, 3.594, and 3.236 respectively, showing that on average, respondents are also approaching the agreed point on the Likert scale. The deviation from the mean of these items was 1.058, 1.14, 1.145, and 1.316. the kurtosis for these items is as follows: -0.236, -0.182, -0.336, -0.019, and the skewness: -0.12, -0.425, -0.186, and -0.256. For the next variable of Beliefs about the future (BAF), the selected items are BAF1 to BAF5, with the relative mean values as 2.614, 2.650, 3.543, 3.551, 3.685. It means the first two items have their average values lower than 3. The Desire for knowledge (DIK) items, DIK1 to DIK4, have the mean scores of 3.382, 3.366, 3.272, and 3.283. The last variable Academic performance (ACP) has two items, ACP1 and ACP2, whose average scores are 3.594 and 3.465. Table 3 summarizes these results.

Table 3: Descriptive Results.

Name	Mean	Scale min	Scale max	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness
AIN1	3.528	1	5	1	5	1.086	-0.63	0.356
AIN2	3.476	1	5	1	5	1.107	-0.252	0.708
AIN3	2.484	1	5	1	5	1.135	-0.502	0.575
AIN4	3.732	1	5	1	5	0.939	-0.126	-0.706
AIN5	3.358	1	5	1	5	1.445	-0.852	0.702
SML1	3.665	2	5	2	5	1.058	-0.236	-0.12
SML2	3.764	2	5	2	6	1.14	-0.182	-0.425
SML3	3.594	2	5	2	6	1.145	-0.336	-0.186
SML4	3.236	1	5	1	5	1.316	-0.019	-0.256
BAF1	2.614	1	5	1	5	1.02	-0.189	0.606
BAF2	2.650	1	5	1	5	1.05	-0.656	0.308
BAF3	3.543	1	5	1	5	1.07	-0.52	0.449
BAF4	3.551	1	5	1	5	1.457	-0.943	-0.725
BAF5	3.685	1	5	1	5	1.399	-0.758	-0.797
DIK1	3.382	1	5	1	5	1.245	-0.684	-0.559
DIK2	3.366	1	5	1	5	1.284	-0.874	-0.441
DIK3	3.272	1	5	1	5	1.262	-0.934	-0.311
DIK4	3.283	1	5	1	5	1.377	-1.155	-0.321
ACP1	3.594	1	5	1	5	1.209	-0.516	-0.673
ACP2	3.465	1	5	1	5	1.202	-0.72	-0.381
Note: Artificial Intelligence (AIN); Smart Learning (SML); Beliefs about future (BAF); Desire for knowledge (DIK); Academic performance (ACP)								

4.3. Measurement Model Results

Table 4 presents Alpha, Composite Reliability (rho_a / rho_c) and Average variance extracted (AVE) of all the five variables of the study, viz., ACP, AIN, BAF, DIK and SML. The alpha values of all variables are 0.813, 0.857, 0.883, 0.890, 0.753, all of which are above 0.70, a criterion for examining the reliability of Cronbach alpha (**Jianjun *et al.***, 2021). The second measure of testing reliability is composite reliability (rho_a) and composite reliability (rho_c) (**Parsaoran; Hartono**, 2023; **Hastuti *et al.***, 2023). The results found that composite reliability (rho_a) for all variables was measured as 0.819, 0.960, 0.886, 0.890, and 0.784, and in terms of Composite reliability (rho_c) is 0.914, 0.883, 0.945, 0.924, and 0.858. As per the given results, none of the values are less than 0.70, hence no issue has been found related to the composite reliability. Average variance extracted (AVE) aims to determine the amount of variance captured by the variables with the variance due to measurement error. An AVE value should be above 0.50 to claim the convergent validity of the given variables (**dos Santos; Cirillo**, 2023; **Hulland**, 1999; **Chen**, 2008). The AVE for variables is 0.842, 0.656, 0.895, 0.751, and 0.668. As we can see, all the variables truly justify their position when accounting for the reliability and convergent validity (See Table 4).

Table 4: Alpha, Composite Reliability and AVE.

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ACP	0.813	0.819	0.914	0.842
AIN	0.857	0.960	0.883	0.656
BAF	0.883	0.886	0.945	0.895
DIK	0.890	0.890	0.924	0.751
SML	0.753	0.784	0.858	0.668

Table 5 presents the results for the HTMT ratio using pair of variables. HTMT ratio is a measure for evaluating the discriminant validity of constructs of a study. The HTMT is a statistical approach and method which is being used to evaluate the level of the discriminant validity in structural equation modeling (**Hair; Alamer**, 2022; **Dirgiatmo**, 2023). This technique is used within Partial Least Squares structural equation modeling. Moreover, HTMT is an up to mark technique of checking the discriminant validity; therefore, it provides a more robust measure to verify if constructs are sufficiently distinct from one another in any of the given model (**Hair; Alamer**, 2022; **Dirgiatmo**, 2023).

For finalizing the presence of the discriminant validity, the HTMT ratio should be less than 0.85 (**Yusoff *et al.***, 2020). Observing the provided results below in Table 5, the pairwise correlation between the AIN <-> ACP, BAF <-> ACP, BAF <-> AIN, DIK <-> ACP, DIK <-> AIN, DIK <-> BAF, SML <-> ACP, SML <-> AIN, SML <-> BAF, and SML <-> DIK was 0.035, 0.451, 0.053, 0.402, 0.040, 0.569, 0.383, 0.041, 0.544, and 0.483 respectively. All of these values are less than 0.85, therefore, the presence of discriminant was proved in this research. Figure 1 confirms these results.

Table 5: Discriminant Validity→HTMT Ratio.

Pair of the Variables	Heterotrait-monotrait ratio (HTMT)
AIN <-> ACP	0.035
BAF <-> ACP	0.451
BAF <-> AIN	0.053
DIK <-> ACP	0.402
DIK <-> AIN	0.040
DIK <-> BAF	0.569
SML <-> ACP	0.383
SML <-> AIN	0.041
SML <-> BAF	0.544
SML <-> DIK	0.483

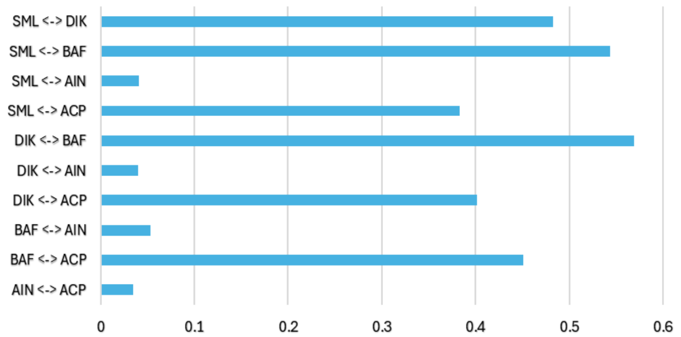

Figure 1: HTMT Ratio.

The Fornell-Larcker Method was also used for discriminant validity. This method is widely used to assess discriminant validity as it ensures that a construct is truly distinct from others in the same model. The true meaning of such discrimination is that it measures a concept not captured by any other latent variable in the model. This technique is widely supported in past studies (**Afthanorhan *et al.***, 2021; **Hilkenmeier *et al.***, 2020). The Fornell-Larcker results are presented using the square root of AVE as a baseline score to compare. The results, depicted using the diagonal series, are 0.918, 0.810, 0.946, 0.867, and 0.818 for ACP, AIN, BAF, DIK, and SML, showing that the square root of AVE is higher than these values. Therefore, the discriminant validity exists. The same has been reiterated in Figure 2.

Table 6: Discriminant Validity→Fornell-Larcker Criteria.

	ACP	AIN	BAF	DIK	SML
ACP	0.918				
AIN	0.040	0.810			
BAF	0.385	0.066	0.946		
DIK	0.769	0.036	0.505	0.867	
SML	0.308	0.017	0.441	0.401	0.818

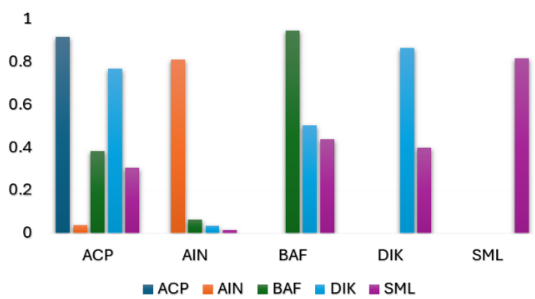

Figure 2: Fornell-Larcker Scores for All Variables.

The third method for evaluating the discriminant validity is loading and cross-loadings (**Rasoolimanesh**, 2022; **Cheung *et al.***, 2024). The scores are well covered in Table 7, where the highlighted values are the items' loadings against the cross-loadings. For example, ACP shows loadings as 0.926 and 0.909 against the relative cross-loadings as 0.013, 0.052, 0.024, 0.008, 0.348, 0.380, 0.669, 0.683, 0.619, 0.694, 0.202, 0.319, and 0.218. The AIN's loadings are 0.804, 0.915, 0.812, and 0.694 for AIN1, AIN2, AIN3, and AIN5 items. The cross-loadings are less than these (i.e., 0.024, 0.051, 0.076, 0.049, 0.089, 0.017, 0.024, -0.002, 0.017, 0.005, and 0.023). The output based on the similar trend for the other variables shows that BAF loadings are 0.943 and 0.950, which are above the cross-loadings. Additionally, DIK1, DIK2, DIK3, DIK4 are with the loadings of 0.865, 0.883, 0.852, and 0.866. SML1, SML2, and SML3 loadings are 0.766, 0.889, and 0.792. The overall results support the presence of discriminant validity. Figure 3 reflects the loadings of the selected items, where those with lower loadings were deleted from the model.

Table 7: Discriminant Validity→Loadings and Cross Loadings.

Variables	ACP1	ACP2	AIN1	AIN2	AIN3	AIN5	BAF4	BAF5	DIK1	DIK2	DIK3	DIK4	SML1	SML2	SML3
ACP	0.926	0.909	0.013	0.052	0.024	0.008	0.348	0.380	0.669	0.683	0.619	0.694	0.202	0.319	0.218
AIN	0.024	0.051	0.804	0.915	0.812	0.694	0.076	0.049	0.089	0.017	0.024	-0.002	0.017	0.005	0.023
BAF	0.398	0.305	0.024	0.106	-0.008	-0.009	0.943	0.950	0.410	0.420	0.448	0.472	0.373	0.392	0.321
DIK	0.740	0.669	0.040	0.034	0.015	-0.007	0.465	0.491	0.865	0.883	0.852	0.866	0.261	0.372	0.337
SML	0.310	0.254	-0.008	0.011	0.052	-0.029	0.434	0.402	0.348	0.353	0.357	0.333	0.766	0.889	0.792

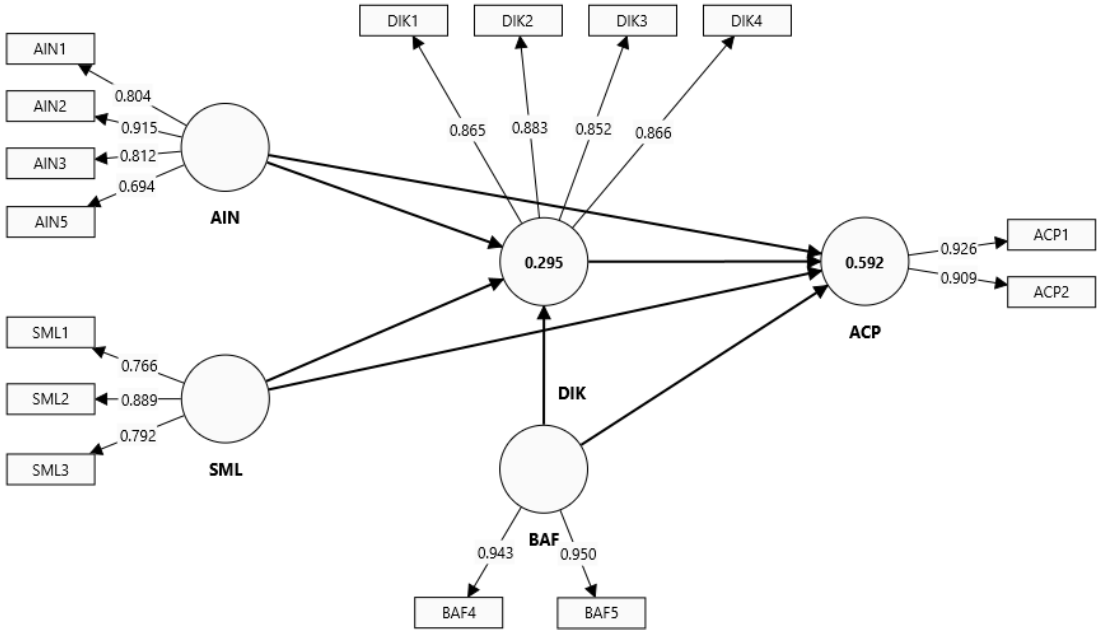

Figure 3: Loadings of the Selected Items.
Note: Items with low loadings were removed

4.4. R-square of the Model

The Model's Explanatory variable was examined using the R-square. The two endogenous variables ACP and DIK reflect their R-square as 0.592 and 0.295. The R-square value for ACP is 0.592, which means that 59.2% of the variance in the ACP construct is explained by the given independent variables in a similar model. This indicates a relatively good fit, implying that the model can account for a significant portion of the variance in ACP. Conversely, the DIK with an R-square of 0.295 shows that the model explains less than 1/3 of the variance, indicating there may be other factors influencing DIK that the current study model does not capture. Adding more variables to a similar model can provide better results. Comparatively, the adjusted R-square is less than what we have achieved under the R-square. Still, the values under the adjusted R-square are also more reliable.

Table 6: R-square.

Details	R-square	R-square adjusted
ACP	0.592	0.586
DIK	0.295	0.286

4.5. Structural Model Results

The structural model results are presented in Table 7 using the directional path of the variables. The study tested the following paths: AIN -> ACP, BAF -> ACP, DIK -> ACP, and SML -> ACP. The results show that the path coefficient between AIN and ACP is 0.118, and the standard deviation is 0.026. This deviation represents the variation in the coefficients across different samples. The positive coefficient of 0.118 implies that AIN positively impacts the ACP. When account for the positive impact of AIN on ACP, a detailed review of the past studies reveals several important aspects. For example, AI by using the ChatGPT makes learning easier for the students by giving them instant access to countless information over the internet. Considering the measurements of the AIN under this research, it has been found that when the students have questions, they get detailed and clear answers, which makes understanding tough topics much simpler. Moreover, the conversational style of using AI tools like ChatGPT feels more engaging compared to reading textbooks, allowing students from different academic fields to interact naturally and learn in a way that fits their academic requirements. This kind of accessibility would reduce the stress of not getting timely answers from other online and offline sources. Therefore, it ultimately boosts their overall academic performance.

Moreover, ChatGPT helps make learning more efficient by breaking down complicated problems and showing different ways to solve them. As a result, this helps the students understand the provided material clearly and improves their ability to understand more critically. Another significant advantage of using the ChatGPT for academic purpose is that it increases students' learning efficiency. It saves students a lot of time by providing quick answers, so there is no need to search through multiple websites or books. This indicates that they can learn more in less time. The results of the present study are consistent with (**Shahzad *et al.***, 2024b), who found that artificial intelligence is positively and significantly related to the students' academic performance.

The second path of the study reflects the relationship between the BAF and students' academic performance. The results show a coefficient of -0.007, a standard deviation of 0.046, and T-statistics of 0.154 as the t-score is less than the minimum threshold level of 1.96. The higher p-value aims to determine that the impact of BAF on ACP is insignificant; hence no relationship exists. The third path of Table 7 indicates that the coefficient is 0.771 with the three stars. This coefficient determines that desire for knowledge is leading to a positive change in the academic performance of the students in China. However, the coefficient in terms of sample mean is found to be 0.768, whereas the standard deviation is 0.047. The study got the T-statistics of this relationship as 16.353, leading to a p-value of 0.000. Both of these values truly represent the DIK's significant impact on the ACP among the similar sample respondents. For measuring the DIK, the study considers four different items and as per the factor loadings, they are well considered for calculating the same constructs. Based on this fact, the study determines the relationship between DIK and ACP through the following interpretation.

The first item of DIK determines “exploring the new ideas”. The desire for knowledge plays a crucial role in driving academic success among students, as highlighted by the given statement. Exploring new ideas is found to be as an essential part of the intellectual capabilities of the students. When students enjoy discovering new concepts, they are more likely to engage deeply with learning material while pushing themselves beyond the mere memorization of the ideas. This desire for discovering some sort of the new ideas and themes often leads to a better grade due to the concern that it makes the students more curious and encourages them to think critically, which are important skills for handling difficult schoolwork. Being excited to learn about unfamiliar topics also shows that students are open to new knowledge, which can help them do better in their studies. Willingness to step out of their comfort zone is a sign of a good student. Exploring new areas helps students see things from different viewpoints and gives them a more complete understanding of different subjects. This attitude also helps them become more adaptable, making it easier to apply what they learn in different situations, which in turn improves their academic success.

The third statement under DIK focuses on the fascinating to learn new information. The fascinating experience of learning new information has a major aim to highlight how a genuine interest towards better academic performance by getting new body of knowledge. When students find some level of happiness while learning new ideas and knowledge, they are more remain more motivated to learn. Additionally, the level of fascination with new information is not just about accumulating facts but also involves understanding their significance, which leads to deeper comprehension and long-term material retention. Finally, under present study investigation, the 4th item under DIK reflects that “enjoy learning something new and finding out more about it”. This attitude ensures that students are not just skimming the surface but are willing to dig deeper into topics, seeking a thorough understanding.

The fourth direct path shows the impact of smart learning on students' academic performance. The positive direction of the coefficient confirms that increasing learning by using smart technologies leads to an improved academic performance among the study’s participants. The relationship was found to be statistically significant at 1%, with a p-value of 0.000. This value is less than 1% to infer that the direction path between SML and ACP is statistically acceptable for which the confidence level is 99%. More specifically, the given confidence means that researchers of the current research are 99% sure to claim that SML improves academic performance.

The above-described relationship has several perspectives. For example, one concept is that smart technologies give the university students various opportunities to expand their knowledge and improve their learning experience as a whole. With tools like online courses, educational apps, multimedia content, and website portals, students can easily learn about a wide range of topics, even those covered by their curriculum. This helps make them an outstanding learner. Additionally, the smart technologies encourage collaboration by allowing students to work together through online forums, virtual classrooms, and other interactive platforms, respectively. Such type of the teamwork not only determines an improvement and understanding among the students but also helps them to grow academically and socially. As a result, there is an increasing trend in the academic performance. Moreover, smart technologies provide personalized feedback and pathways based on the adaptive learning that help the students pinpoint their weaknesses. This specialized aid gives university students an edge over their peers and helps improve their academic results.

Additionally, the smart technologies also make learning phase for the students as more enjoyable, which has a big impact on their success. Using interactive multimedia and customized content, these tools turn several academic challenges into engaging, easy-to-understand experiences for the students. When learning becomes enjoyable, the student community feels more motivated, leading to better understanding and retention of what they will learn by utilizing the smart technologies and related devices. Additionally, smart technologies make it easier to learn new practical skills. These skills include using software tools, data analysis, and other online interactive tutorials. This not only boosts the academic abilities of the university students but also prepares them for future challenges. Overall, the exploration of the diverse topics, learning in groups, personalized improvements, and having an enjoyable experience makes smart technologies an effective and a strategic way to enhance the academic performance of the university students significantly, and the same has been experienced in this study.

The current literature also supports the way smart learning and technologies are linked with the academic performance. **Seo *et al.*** (2016) have examined the relationship between smart learning and technologies with the academic output. The results recommend that smart learning programs are effective enough to increase the nursing students' academic achievements, class satisfaction, and critical thinking. **Biwer *et al.*** (2023) have also focused on the effective and smart learning strategies. The overall debate and literature evidence infers that smart learning is a positive indication of increasing academic performance among university students in Chinese regions. Table 7 presents the analysis of all directional paths.

Table 7: Direct Path Analysis.

Relationships	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AIN -> ACP	0.118***	0.116	0.026	4.538	0.000
BAF -> ACP	-0.007^{NS}	-0.007	0.046	0.154	0.877
DIK -> ACP	0.771***	0.768	0.047	16.353	0.000
SML -> ACP	0.105***	0.104	0.017	6.176	0.000

The DIK's specific indirect or mediating effect on the relationship between independent and dependent variables have been well presented using the outcomes in Table 8. This table has several outputs including the coefficient, deviation of the coefficient, T-statistics, and P-values. Using all these values as a base of analysis and subsequent discussion, the provided output first explores the mediating effect of DIK between SML and ACP. The path has been depicted as SML -> DIK -> ACP. It means that SML approaching to DIK and DIK finally approaching to ACP. The coefficient of this path is 0.171 in terms of original sample, meaning that positive relationship exists in this path. Moreover, t-score is found to be as 3.559, leading to a p-value of 0.000. Observing all of these values, it is determined that the mediating path of DIK between SML and ACP is statistically significant and positive.

However, whether this mediation is partial or full, this study focuses on the direct path between SML and ACP when there is no mediating effect and again the direct path between both when the DIK has been added as a mediator. For example, the direct path between SML and ACP without any mediating analysis was highly significant and positive, with a coefficient of 0.105. It means that when there is no mediation, smart learning technologies is positively and significantly connected with the academic performance. After adding the DIK, the output Figure 4 shows that the p-value was found to be 0.979, which is insignificant at 5%. As the addition of the DIK tends to cause an insignificant relationship between SML and ACP, its mediating effect is full. It reflects that there is a full mediating effect of DIK between SML and ACP.

When university students want to learn, they are likelier to make the most of smart learning technologies. Additionally, interactive learning platforms, educational online applications, and adaptive learning tools can provide personalized experiences that accommodate similar students' curiosity and learning style. A student-driven by a genuine desire to explore and understand will engage more deeply with these technologies, spending time digging into different subjects, finding extra resources, and using these tools to enhance their understanding.

Therefore, the thirst for knowledge among the students help them to use smart learning tools more effectively, which in turn boosts their academic engagement and performance outlook. Additionally, the active utilization of stated tools helps to satisfy their curiosity regarding the learning of new concepts, they become better at grasping complex topics while retaining information. In this way, the desire for knowledge serves as a link between using smart learning tools and academic success, making these technologies more impactful. Based on the given arguments and specifically the empirical relationships, it has been inferred that DIK tends to mediate the relationship between smart learning and the academic performance of the university students. However, the results provide insignificant outcome for the mediating role of DIK between AIN and ACP.

The third mediating effect of the DIK has been tested between the BAF and ACP. The results are positively significant, showing that the coefficient is 0.314 and the p-value is 0.000. This relationship is significant at 1%; hence, evidence exists that a significant mediating effect from the DIK between BAF and ACP exists. This relationship implies that the desire for knowledge among the student aims to play a key role in linking students' beliefs about their future with their academic performance factor by turning their hopes into concrete actions. When university students have positive thoughts about their future and related objectives, such as wanting to reach their career goals or imagining themselves in successful roles, they feel more motivated to excel their studies and learning.

However, being motivated is not always enough, as it needs to be channeled into actual learning efforts and capabilities, and this is point where the desire for knowledge makes a difference in terms of academic success. It pushes the university students to actively engage with their studies, turning their aspirations into real academic progress and success. Therefore, it was found that the DIK has a significant mediating effect on BAF and ACP. However, this mediating effect is also regarded as full mediation, as with the presence of the DIK, the direct path between BAF and ACP has been found as statistically significant as defined by the p-value of 0.903. All these results are presented in Table 8 and Figure 4.

Table 8: Specific Indirect Effect.

Specific Path of DIK	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SML -> DIK -> ACP	0.171	0.173	0.048	3.559	0.000
AIN -> DIK -> ACP	0.004	0.011	0.056	0.077	0.938
BAF -> DIK -> ACP	0.314	0.312	0.051	6.214	0.000

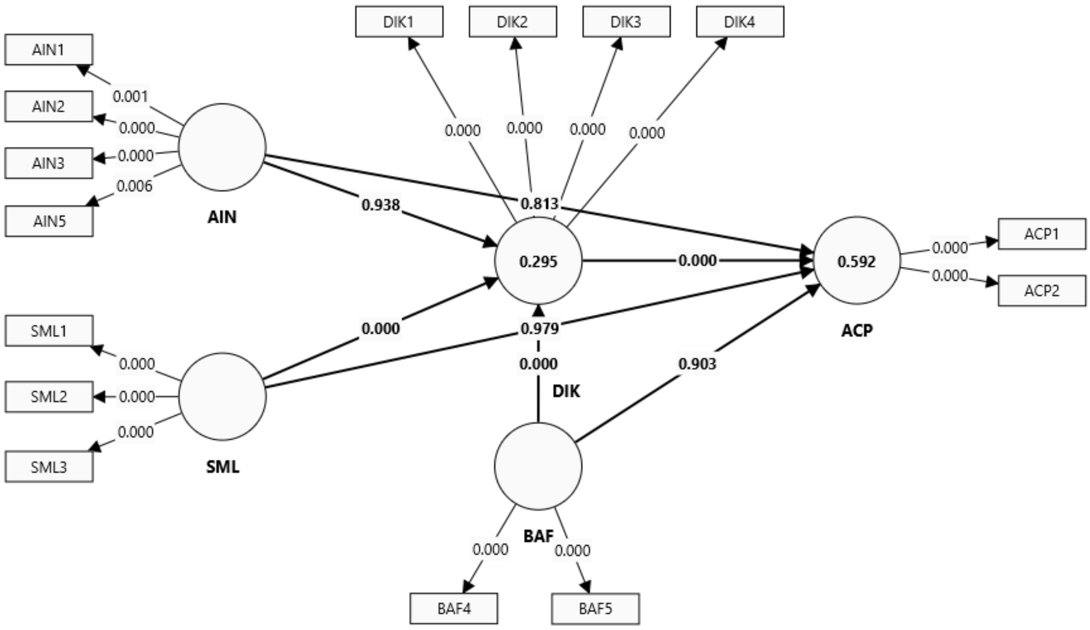

Figure 4: Mediating Analysis Findings.
Source. Authors use of Smart PLS (4th version)

5. Conclusion

This study examines the direct influence of artificial intelligence, smart learning, and beliefs about the future on the academic success/performance of university students in China. The results reveal several major findings. First, students observe that artificial intelligence significantly affect their academic performance. Second, using smart learning techniques aims to boost the academic performance among the same respondents. Third, desire for knowledge is among the major indicators of promoting academic success among students with mixed demographic dimensions. Fourth, testing the mediating effect of the desire for knowledge shows that it positively and significantly mediates between the smart learning and academic performance and between beliefs about the future and academic performance for the same students in China. The policymakers, linked with the Chinese universities, are given a clear, well-supported plan to help them understand and manage the key role players of the student's academic performance, specifically in terms of smart learning, artificial intelligence and desire for knowledge. This guidance adds to our academic work and aims to drive meaningful action toward adopting technology that benefits people. The suggested policies include but not limited to put the investment in digital infrastructure, training and development of the academic staff with key focus on the digital tools and technologies in education, provision of financial support for digital integration in the universities, encouraging the research and development among the educational institutions, respectively.

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