

The Dual Nature of Generative AI in Inclusive Education: Investigating the Role of AI in Students with Disabilities' Empowerment, Dependence, and Academic Participation

Dr. Meera M S¹

¹ Associate Professor, Department of Business Administration

SCMS School of Technology and Management, Kochi, India

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Generative AI has made its way into classrooms and university campuses before the completion of studies necessary to understand its impact on students with disabilities, a group which might benefit the most from such technology. The present paper aims to develop a structural model illustrating how AI carries positive and negative consequences in the context of inclusive education. This will be facilitated through the development of two parallel paths along which AI impacts students with disabilities, the empowerment path and the dependence path. The former relies on the fact that AI is accessible to students, makes it possible for them to obtain additional assistance while studying, which leads to increasing their learning efficiency and engagement into different academic processes. The latter path assumes that students of higher education institutions, being dependent on the use of AI tools, have to offload cognitive processes making them weaker learners. Finally, the paper examines the role of AI literacy in the mediation of the relationship between accessibility of AI and dependence on it. The relevance of the paper is justified by the presented academic literature review for 2022 and afterwards, as well as the design of ten hypotheses and the explanation of the methodology to be applied using SmartPLS 4 software for the analysis of primary data obtained from surveys of students with disabilities in India. The paper includes full examinations of the measurement model and structural hypotheses. Moreover, the conceptions of Self-Determination Theory and Cognitive Load Theory will be presented to justify each hypothesis of the study. The final part of the paper will depict the summary of the findings and determine the significance of studying the AI impact on the inclusive teaching process.

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1. Introduction

The rapid multiplication of generative artificial intelligence tools since the release of ChatGPT to the public at the end of 2022 changed students' reading, writing, problem-solving and revision strategies around the world. The transition from useless gadget to indispensable part of everyday routines of students of various degrees took place in just a few months. The discussion in the higher educational institutions later revolved around the questions of academic honesty and the nature of assessments as well as improvement/decline of critical thinking skills due to the use of generative AI. In contrast, students with disabilities see the situation concerning the advent of generative AI differently than other students, as they were used to struggling with accessibility of education beforehand given its inability to solve this problem for many years. Technologies that have previously emerged such as text-to-speech solutions, screen readers and adaptive content platforms have already shown how technology could help people with disabilities and generative AI made a huge leap forward because it is not only the instance of technology that could allow turning complex academic literature to plain text, but also divide complex assignments into small tasks and provide thorough explanations without making students lose face. All the statements above be not only theory but also supported by contemporary data. However, the properties that cause generative AI to be appealing as an assistive and explanatory instrument, such as accessibility, the ability to simplify complexity and readiness to finish a task at the request of a student instead of just facilitating the student's own activity, result in a real danger as well: in the long run, there is a shift of cognitive work from a learner to a tool. Researchers have started to call it cognitive offloading and, if the shift is repeated on a regular basis instead of being something periodic, it can also be called cognitive reliance. This dualistic nature is important beyond a few use cases. The concept of generative AI in education is quite the opposite due to the fact that the same action that greatly reduces the cognitive

burden of a learner can, at the same time, provide another learner with an absolute impossibility to engage mentally in the activity involved, given that the same process allows a learner to transfer the cognitive work to the device.

This situation is pertinent to students with disabilities, who may be affected by heavy cognitive demands. Thus, it is necessary to study the use of generative AI in this specific group of people, rather than to consider them in general studies of AI. Students with disabilities include various categories of people, ranging from students in need of special education to those who can be classified as having developmental disabilities, physical disabilities, etc. Overall, different categories of these students would utilize the advantages of generative AI in a different manner. In India, there exist policies aimed at helping people with disabilities, though a lot needs to be done for their implementation and realization. For instance, the Rights of Persons with Disabilities Act appeared recently so that a greater commitment to inclusiveness would need time for all institutions committed to it to be ready. Generative AI is a technology not controlled by educational institutions, which makes it interesting to study the implications of using it by students with disabilities in India. Moreover, current methods of assisting students with disabilities have to deal with the use of traditional accommodations. Generative AI brings about many more complicated questions that arise due to the absence of clear guidelines on how to use the innovation.

2. Review of Literature

2.1 Generative AI and Students with Disabilities

Research on generative AI among students with disabilities has been on the rise since 2023. According to the report by Pierrès et al. (2025), the study based on semi-structured interviews reported the advantages of generative AI helping the learners with easier understanding and providing an opportunity to learn according to their way, in accordance with the basic principles of Universal Design for Learning (UDL). The research by Sakowicz and Hamidi (2025) demonstrated similar

findings with the use of the UDL framework, which allows seeing the richness of possible kinds of involvement, representation, and expression. The research by Zhao, Cox, and Chen (2025) based on 124 proper responses provided by the students with disabilities like having ADHD or dyslexia has shown the usage of generative AI chatbots for various writing tasks. However, the students mentioned some issues referring to untrustworthy results, academic honesty, and subscription fees still having the wish to engage in the development of AI policy.

Another study conducted by Zhao, Chen, and Cox (2025) mentioning explainability, expressibility, and plannability as three affordable features facilitating the writing process of students with disabilities, which also point at the lack of motivation and poor time-management skills. The point of view of Wells (2025) adds an institutional dimension to the research arguing that AI can bridge the persistent gaps in disability services and accommodations. This is in the line with the individual cases since generative AI acts as more than just a personal solution for the problem, especially in the countries like India where official support related to disability is not so common. The outcome of the studies in assistive technology proves that it is worth using technology applied to structured pedagogy rather than separately (Yenduri et al., 2023). In a similar way, UNESCO (2023) states that use of the technology in education leads to better success in graduation and raising one's self-esteem.

2.2 Cognitive Offloading, Dependence, and Learner Autonomy

A new research field has arisen analyzing cognitive impacts of generative AI (GAI) from the standpoint of Cognitive offloading, which refers to a process of offloading cognitive tasks onto external tools that would have been performed internally. Fan et al. (2024) studied a group of Chinese students and identified that those using ChatGPT, as compared to the group of students relying on human experts, writing-review tools, or the ones that did not seek any assistance showed little self-regulated learning in the process of revising their papers, especially in terms of evaluation and orientation. The researchers called this phenomenon the concept of

"metacognitive laziness," proving that reliance on AI tools gets students accustomed to the outputs made by AI. However, the same cognitive offloading can also lead to positive effects. Zhang et al. (2026) conducted a study on 936 undergraduates from six Chinese colleges and found that the intensity of GAI usage was positively correlated to the perceived academic creativity levels while cognitive dependency formed a negative correlation. This leads to the conclusion that dependence and empowerment may coexist with one another. The authors of the study also identified a negative correlation between AI literacy and cognitive dependence. A comparable study was conducted by Iqbal et al. (2025) who analyzed GAI use in 465 pre-service teachers and came to the conclusion that it is correlated with academic success through shared metacognition and cognitive offloading, thereby demonstrating the ability to free cognitive resources for higher cognitive tasks instead of substituting them alone. The paradox is further explained by Wang et al. (2026) in their review of GAI, cognitive offloading and learner agency in higher education. The authors observed that the educational outcomes depended less on the GAI itself than on pedagogical design and patterns of use.

2.3 AI Literacy as a Moderating and Differentiating Factor

A separate area of study recognizes AI literacy, which refers to the capability to utilize, assess and implement AI outputs, as a crucial factor that distinguishes positive from negative results of generative AI. The study conducted by Chen and Xiao (2025), based on the feedback from 645 university students, stated that exposure to AI outputs positively related to the enhancement of creativity via cognitive flexibility, although the correlation occurred mainly for students with a moderate to high level of AI literacy. This means that AI literacy serves as a threshold condition that decides whether generative AI results in empowerment or dependence. As per Self-Determination Theory (SDT), it is also suggested that AI literacy is connected to the satisfaction of psychological needs. Wut, Sum, and Wong (2025), who studied the data from 30 higher

education institutions in Hong Kong, found out that there is a positive relationship between AI literacy and autonomy and competence as well as between AI literacy and the intention to use AI in the profession. This study focused on the teachers and therefore serves as the groundwork for further exploration of the effect of AI literacy on students' autonomy and competence thus determining whether generative AI serves as a helper or obstructer in learning.

2.4 Cognitive Load Theory and the Design of AI-Supported Learning

Cognitive Load Theory (CLT) offers useful insights on the differential effects generative AI has on multiple users and tasks. Qian et al. (2026) stress that the influence of CLT on intrinsic, extraneous, and germane load largely hinges on such variables as AI support level and the frequency of its employment, as well as the characteristics of the given task and learner's previously acquired knowledge. Of the 16 studies that explored extraneous load, seven indicated that AI made the information less complicated, while only one research pointed to an increase in extraneous load. The situation with germane and overall load is not so straightforward; therefore, one should not jump to the conclusions about the ability of generative AI to always decrease cognitive load. This difference is extremely important for the representatives of the disabled community. AI has all the chances to minimize extraneous load by simplifying or reorganizing the information, making it possible to free the cognitive resources necessary for germane processing. However, too much reliance may prevent an individual from exerting the necessary efforts to mastering vital academic skills. Thus, the impact of the same AI application may either enhance or interfere with learning depending on how it is used. This shows that in order to benefit from the use of AI one has to master AI literacy, self-efficacy, and autonomy.

2.5 Synthesis of the Literature

Combining these four areas of literature points to the need to realize that there is no such thing as a simple single-outcome statement regarding generative AI's effects on students with disabilities. In particular, specific literature from the disability framework discussed in subsection 2.1 shows that

generative AI leads to real, The second literature framework, cognitive offloading literature researched in subsection 2.2, indicates that while the mentioned advantages are noteworthy, there exists a clear risk of the negative consequences in the form of the dependency and reduced self-regulation of engagement, which can be counterbalanced by certain studies focusing on the offloading of unnecessary cognitive impacts. In addition, the generative AI literacy literature presented in subsection 2.3 points to the fact that not all students possess the ability to benefit from the use of AI since the students might have different skills along these lines. Finally, the cognitive load theory literature voiced in subsection 2.4 shows that even the same tool may produce counterintuitive results and needs to account for different levels of cognitive load in the task. What is surprising is that none of the researchers in the field of generative AI studies this problem from the angle of students with disabilities and considers the experience of India where the solutions in this area are still underdeveloped.

2.6 Research Gap, Objectives, and Hypotheses

The current literature suggests that generative AI can improve accessibility and engagement among students with disabilities but can also lead to cognitive offloading and dependence. AI literacy seems to play a role in whether students experience empowerment or cognitive dependence. These relationships, however, have not been systematically studied using an integrated structural model that focuses on students with disabilities. The majority of the research reviewed concerns the general student population, especially undergraduates from Asia, and disability has often not been taken into account. The studies specifically looking at students with disabilities have mostly been using qualitative interviews and descriptive surveys instead of structural models that look at direct, indirect, and moderation relationships. This work fills this gap by proposing a structural model that looks at the pathways of empowerment and dependence using the Self-Determination Theory and the Cognitive Load Theory. The other gap is related to geographical and institutional context. Most of the available studies belong to the countries including China, the UK, Switzerland, and Hong Kong, and they present very

few data about Indian higher education. This is especially important because of India's policy commitment to disability inclusive education and ongoing limitations in providing institutional support for accessibility. By collecting original data from students with disabilities in Indian universities, this work provides local evidence of how generative AI can drive empowerment and cognitive dependence at the same time

3.1 Objectives of the Study

Against these gaps, this study pursues the following objectives. First, to examine the empowerment pathway running from AI accessibility through AI learning support and learning self-efficacy to academic engagement. Second, to examine the dependence pathway running from AI accessibility through AI dependence, cognitive offloading, and learning autonomy to academic engagement. Third, to test whether AI literacy moderates the relationship between AI accessibility and AI dependence, thereby functioning as a differentiating factor between the two pathways. Fourth, to compare the relative strength of the empowerment and dependence pathways in predicting academic engagement among students with disabilities, and to interpret the resulting pattern through Self-Determination Theory and Cognitive Load Theory. Fifth, in order to place this examination within the framework of higher education in India, because of an unavailability of primary evidence through quantitative methods with regard to the application of generative AI by disabled students in India.

3.2 Constructs

The model described for the purpose of achieving the specified aims is made up of eight constructs that can be found in Table 1 of Section 6.1. AI accessibility (AA) presents the exogenous construct denoting students' views regarding the extent to which generative AI systems make academic material and tasks easier for them. AI learning support (ALS) and learning self-efficacy (LSE) comprise sequential mediators on the empowerment route. AI dependence (AID), cognitive offloading (CO), and learning autonomy (LA) act as sequential mediators on the dependence route. AI literacy (AIL) is the moderator of the

route from AI accessibility to AI dependence. Academic engagement (AE) acts as the endogenous outcome construct predicted directly by learning self-efficacy and learning autonomy.

3.3 Hypotheses

Ten hypotheses follow directly from the model specified in Section 3.2 and from the theoretical and empirical literature reviewed in Section 2.

H1: Artificial Intelligence Accessibility has beneficial effects on the AILS.

H2: Artificial Intelligence Learning Support positively influences Learning Self-efficacy.

H3: Learning Self-efficacy acts positively on academic engagement.

H4: Artificial Intelligence Accessibility has direct positive effects on AI dependence.

H5: AI Dependence acts on Cognitive Offloading benefiting it.

H6: Cognitive Offloading impacts Learning Autonomy negatively.

H7: Learning Autonomy influences Academic Engagement positively.

H8: AI Learning Support and Learning Self-efficacy influence each other between AA and AE in the pathway of empowerment between AA and AE through AILS and LSE.

H9: The chain of relationships between Artificial Intelligence Accessibility and Academic Engagement determined in the path of dependence: AA leads to AID, AID leads to CO, and CO leads to LA.

H10: The level of AI literacy moderates the association between accessibility and dependence on AI so that the beneficial influence of AI accessibility on dependence becomes less evident as AI literacy becomes higher.

H1-H7 explain the direct effects on structure; Hypotheses H8 and H9 are concerned with plural mediators leading to empowerment and dependence pathways; Hypothesis H10 specifies the moderating role of AI literacy that Section 2.3 identifies as the principal differentiating factor between the two pathways.

4. Research Methodology

For this research, the researchers have utilized quantitative cross-sectional surveys which were examined by Partial Least Squares Structure Equation Modelling.

4.1 Population and Sampling

The target group includes students with disabilities that are enrolled in Indian institutions of higher education and have utilized at least one generative AI tool in learning. In this study purposive and snowball sampling are used within the framework of the structured questionnaire that was distributed and delivered through the disability support offices, associations of students with disabilities and networks of inclusive education of participating institutions along with referrals from initial respondents. To be eligible to participate in the study, students must self-identify as disabled according to the Rights of Persons with Disabilities Act and should be enrolled in an undergraduate, graduate, or doctoral program and indicate that they used a generative AI tool for their studies in the previous academic term.

The minimum sample size is derived from the inverse square root method that is recommended for PLS-SEM application (Hair et al., 2022) that the current design is aimed for higher usable sample size of at least 200 participants.

4.2 Measurement Instrument

The target of this questionnaire is measuring the 8 constructs using a reflective multi-item 5-Likert scale with the scale anchors laid from strongly disagree to strongly agree. The concept has five items and for the measurement of academic engagement 6 items have been used for the measurement of behaviour, cognition, and emotion as per the literature. The item wording for AI literacy has been borrowed from the AI literacy scales previously validated within the conducted studies (Wang et. al, 2023; Laupichler et al., 2023), referring to the critical evaluation and verification of the content coming from AI in order to distinguish those who are empowered from those who are dependent on AI.

4.3 Ethical Considerations and Limitations

Informed consent, voluntarily participating and the right to opt out are the requirements of the approved protocol. Furthermore, consent papers and questionnaires are user-friendly and in compliance with assistive technologies like screen readers. Nonetheless, there are limitations of the research. The use of purposive and snowball methods of sampling may undermine the generalizability of the results. Additionally, the cross-sectional design restricts the conclusions about the time and cause effects of the variables. Self-reporting in terms of AI offloading and dependency may introduce biases that are related to the same method. Lastly, the moderation and subgroup analyses depend on the adequacy of the sample size used.

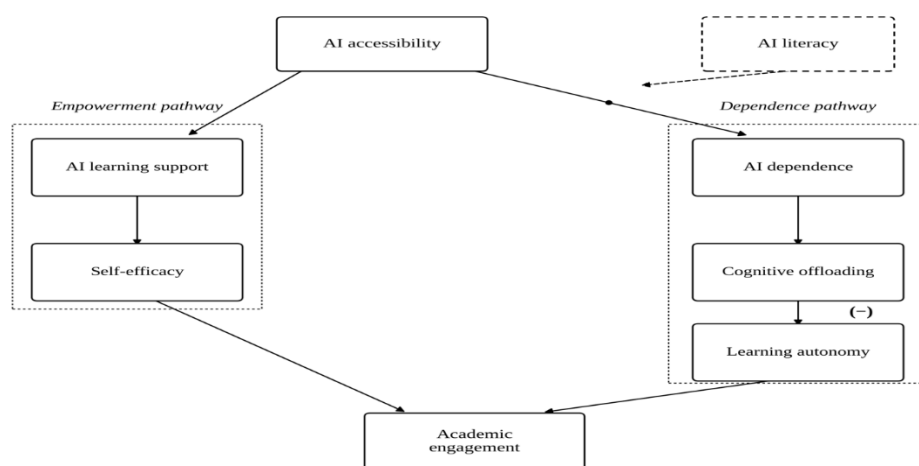


Figure. 1. Conceptual Model (Source: Authors)

The conceptual model explored in this research is illustrated in the diagram presented, showing AI accessibility as the independent construct that affects two parallel paths to academic engagement. The empowerment path passes from AI accessibility to AI learning assistance and learning self-efficacy, while the dependence path passes from AI accessibility to AI dependence, cognitive offloading, and learning autonomy, with the negative effect of cognitive offloading on learning autonomy demonstrated based on the reviewed literature on metacognitive laziness and cognitive dependence in Section 2.2 of the text. AI literacy has been indicated as the moderating variable in the AI accessibility to the AI dependence process, especially considering that it is viewed as the main discriminating factor between empowerment and dependence processes

6. Results

6.1 Constructs, Data Screening, and Respondent Profile

The model looks into the impact of AI accessibility (AA) on the academic engagement (AE) through two distinct pathways: one of them is the empowerment path which consists of AI teaching support, self-efficacy in learning processes, and freedom of action, and the other one is the dependence path which includes dependence on AI and cognitive offloading. The concept of AI literacy (AIL) serves to moderate the relationships mentioned above, which can reinforce or weaken the consequences pertaining to AI.

Table 1. Constructs and Measurement Summary

Construct	Code	Items	Model role	Expected direction
AI accessibility	AA	5	Exogenous	—
AI learning support	ALS	5	Mediator	Positive
Learning self-efficacy	LSE	5	Mediator	Positive
AI dependence	AID	5	Mediator	Positive
Cognitive offloading	CO	5	Mediator	Positive
Learning autonomy	LA	5	Mediator	Positive
AI literacy	AIL	5	Moderator	Moderating
Academic engagement	AE	6	Endogenous	—

Table 2. Respondent Profile

Variable	Category	n	%
Gender	Male	78	39
	Female	120	60
	Other / prefer not to say	2	1
Age	18–20	62	31
	21–23	86	43
	24–26	31	15.5

	27–30	13	6.5
	Above 30	8	4
Education level	Undergraduate	127	63.5
	Postgraduate	55	27.5
	PhD	18	9

Table 3. Generative AI Usage Profile

Variable	Category	n	%
Frequency of use	Less than once/week	12	6
	1–2 times/week	23	11.5
	3–4 times/week	48	24
	5–6 times/week	41	20.5
	Daily	76	38
Primary GenAI tool / use	Concept understanding	130	65
	Writing / language support	140	70
	Research assistance	70	35
	Data analysis	25	12

6.2 Descriptive Statistics

Table 4. Descriptive Statistics of Constructs

Construct	Mean	SD	Skewness	Kurtosis
AI accessibility	3.86	0.78	-0.42	-0.31
AI learning support	4.02	0.69	-0.61	0.18
Learning self-efficacy	3.74	0.73	-0.35	-0.22
AI dependence	3.21	0.91	0.08	-0.57
Cognitive offloading	3.18	0.88	0.11	-0.44
Learning autonomy	3.63	0.76	-0.27	-0.18
AI literacy	3.69	0.71	-0.33	0.02
Academic engagement	3.81	0.68	-0.40	-0.10

Based on the findings, a positive perception regarding the AI accessibility and AI learning

assistance reported by the respondents, as well as Reported learning self-efficacy, AI literacy, and

academic engagement appears to be relatively high. However, the AI reliance and cognitive offloading appear to be relatively lower. The degree of skewness and kurtosis of these metrics further

suggests that the analysis of measurement model and structural model can be conducted in the subsequent phases of the analysis.

Table 5. Outer Loadings

Construct	Item	Loading	Decision
AA	AA1	0.812	Retain
AA	AA2	0.764	Retain
AA	AA3	0.847	Retain
AA	AA4	0.791	Retain
AA	AA5	0.736	Retain
ALS	ALS1	0.821	Retain
ALS	ALS2	0.856	Retain
ALS	ALS3	0.793	Retain
ALS	ALS4	0.814	Retain
ALS	ALS5	0.778	Retain
LSE	LSE1	0.781	Retain
LSE	LSE2	0.826	Retain
LSE	LSE3	0.804	Retain
LSE	LSE4	0.762	Retain
LSE	LSE5	0.839	Retain
AID	AID1	0.801	Retain
AID	AID2	0.774	Retain
AID	AID3	0.836	Retain
AID	AID4	0.759	Retain
AID	AID5	0.815	Retain
CO	CO1	0.793	Retain
CO	CO2	0.821	Retain
CO	CO3	0.768	Retain
CO	CO4	0.846	Retain
CO	CO5	0.784	Retain
LA	LA1	0.776	Retain
LA	LA2	0.812	Retain

LA	LA3	0.741	Retain
LA	LA4	0.829	Retain
LA	LA5	0.795	Retain
AIL	AIL1	0.803	Retain
AIL	AIL2	0.841	Retain
AIL	AIL3	0.788	Retain
AIL	AIL4	0.824	Retain
AIL	AIL5	0.817	Retain
AE	AE1	0.761	Retain
AE	AE2	0.798	Retain
AE	AE3	0.823	Retain
AE	AE4	0.774	Retain
AE	AE5	0.846	Retain
AE	AE6	0.789	Retain

6.3 Measurement Model Assessment

The entire set of 36 measures was taken into account with loading values in the range of 0.736–0.856. As every measure has crossed the accepted limit of 0.70, its suitability has been confirmed. The results suggest that the measures have appropriately represented the relevant concepts and will serve as a solid basis for further PLS-SEM analysis. The values of Cronbach's alpha, rho A, and

composite reliability are from 0.861–0.899, 0.865–0.901, and 0.899–0.924, respectively, which allows us to prove a satisfactory level of internal consistency. AVE values range from 0.640 to 0.709, which is higher than 0.50 and proves a successful convergent validity for all constructs. The correlations among inter-constructs are lower than the square roots of the respective AVE indicating an acceptable level of discriminant validity of the constructs

Table 6. Construct Reliability and Convergent Validity

Construct	Cronbach's α	rho_A	Composite reliability	AVE
AI accessibility	.884	.887	.918	.691
AI learning support	.899	.901	.924	.709
Learning self-efficacy	.872	.875	.906	.659
AI dependence	.881	.884	.913	.677
Cognitive offloading	.875	.878	.908	.663
Learning autonomy	.861	.865	.899	.640
AI literacy	.890	.893	.918	.692
Academic engagement	.888	.891	.915	.643

Table 7. HTMT Discriminant Validity

	AA	ALS	LSE	AID	CO	LA	AIL	AE
AA	—	.64	.51	.58	.46	.41	.49	.55
ALS	.64	—	.72	.54	.48	.62	.57	.68
LSE	.51	.72	—	.43	.39	.70	.48	.74
AID	.58	.54	.43	—	.76	.62	.59	.41
CO	.46	.48	.39	.76	—	.78	.55	.38
LA	.41	.62	.70	.62	.78	—	.61	.72
AIL	.49	.57	.48	.59	.55	.61	—	.52
AE	.55	.68	.74	.41	.38	.72	.52	—

Table 8. Inner VIF Collinearity Assessment

Endogenous construct	Predictor	VIF
AI learning support	AA	1.000
Learning self-efficacy	ALS	1.000
AI dependence	AA	1.342
AI dependence	AA × AIL	1.417
Cognitive offloading	AID	1.342
Learning autonomy	CO	1.000
Academic engagement	LSE	1.782
Academic engagement	LA	1.782

The values of VIF are between 1.000 and 1.782, which is lower than the generally accepted limit of 3.0. Therefore, it can be assumed that multicollinearity is not an issue for predictor constructs in the structural model. The maximum VIF of 1.782 was for LSE and LA on Academic Engagement, while the VIF of 1.417 was for the interaction term AI Dependence × AI Literacy. Overall, the findings show that the predictor constructs are sufficiently different from each other; thus, the model is free from the issue of collinearity.

6.4 Structural Model Assessment

Table 9 reports the direct effects corresponding to H1 through H7, including path coefficients, standard errors, t-values, p-values, 95 per cent confidence intervals, and f^2 effect size. The findings yielded by the structural model support the seven proposed relationships. The accessibility of AI (AA) has a positive and significant impact on the support of learning with AI (ALS) ($\beta = .524$, $p < .001$), and ALS positively impacts self-efficacy in learning (LSE) ($\beta = .447$, $p < .001$). LSE positively influences academic engagement (AE) ($\beta = .312$, $p < .001$). In addition, the AA also positively impacts the

dependency on AI (AID) ($\beta = .286$, $p = .002$), which has a high positive effect on cognitive offloading (CO) ($\beta = .558$, $p < .001$). However, the CO has a negative effect on learning autonomy (LA) ($\beta = -.314$, $p < .001$), while LA positively influences AE ($\beta = .391$, $p < .001$). At the same time, confidence intervals of the results for all examined paths do not include zero

confirming significance, while f^2 values show difference in strength. Thus, H1–H7 are proved to be true.

Table 9. Structural Model Direct Effects

H	Path	β	SE	t	p	95% CI	f^2	Decision
H1	AA $\rightarrow$ ALS	.524	.071	7.38	<.001	[.384, .661]	0.379	Supported
H2	ALS $\rightarrow$ LSE	.447	.083	5.39	<.001	[.286, .608]	0.247	Supported
H3	LSE $\rightarrow$ AE	.312	.082	3.80	<.001	[.151, .469]	0.111	Supported
H4	AA $\rightarrow$ AID	.286	.094	3.04	.002	[.102, .469]	0.087	Supported
H5	AID $\rightarrow$ CO	.558	.067	8.33	<.001	[.425, .688]	0.452	Supported
H6	CO $\rightarrow$ LA	-.314	.091	3.45	<.001	[-.487, -.130]	0.121	Supported
H7	LA $\rightarrow$ AE	.391	.088	4.44	<.001	[.218, .561]	0.172	Supported

6.5 Mediation Analysis

In the analysis of mediation, it is found that AI accessibility (AA) plays a key role in leading to a significant positive indirect effect on academic engagement (AE) via AI Learning and Support (ALS) and learning self-efficacy (LSE) ($\beta = .073$, $SE = .025$, $t = 2.92$, $p = .004$). The confidence interval of 95% [.029, .126] shows that the effect is significant. Hence, H8 is accepted and a set of AA $\rightarrow$ ALS $\rightarrow$ LSE $\rightarrow$ AE was validated.

The findings arising from mediation analysis reveal that AI Accessibility (AA) has meaningful indirect impacts on Academic Engagement (AE) operating through several mechanisms. Nonetheless, the indirect effects involving AI Learning Support (ALS), taken individually, are also significant ($\beta =$

.084, $p = .003$; 95% CI [.034, .143]), indicating that ALS mediates the association between AA and AE. Besides, the indirect effect via the pathway AA $\rightarrow$ ALS $\rightarrow$ LSE $\rightarrow$ AE is significant ($\beta = .073$, $p = .004$; 95% CI [.029, .126]), indicating the presence of sequential mediation so that AA influences AE via ALS and LSE. Additionally, the link AA $\rightarrow$ LSE $\rightarrow$ AE is established ($\beta = .046$, $p = .029$; 95% CI [.007, .090]), showcasing mediating role of LSE in the relationship of AA and AE. Since all confidence intervals do not include zero, indicating that all three indirect effects are statistically significant, it can be concluded that AI accessibility is associated with academic engagement both through single mediation and through the sequential mediator.

Table 10. Serial Mediation Empowerment Pathway

H	Indirect path	β	SE	t	p	95% CI	Result
H8	AA $\rightarrow$ ALS $\rightarrow$ LSE $\rightarrow$ AE	.073	.025	2.92	.004	[.029, .126]	Supported

Table 11. Specific Indirect Effects Empowerment Pathway

Path	β	SE	t	p	95% CI
AA $\rightarrow$ ALS $\rightarrow$ AE	.084	.028	3.00	.003	[.034, .143]
AA $\rightarrow$ ALS $\rightarrow$ LSE $\rightarrow$ AE	.073	.025	2.92	.004	[.029, .126]
AA $\rightarrow$ LSE $\rightarrow$ AE	.046	.021	2.19	.029	[.007, .090]

Table 12. Serial Mediation Dependence / Cognitive Offloading Pathway

H	Indirect path	β	SE	t	p	95% CI	Result
H9	AA $\rightarrow$ AID $\rightarrow$ CO $\rightarrow$ LA $\rightarrow$ AE	.020	.010	2.00	.046	[.002, .041]	Supported

The mediation analysis indicates that AI Accessibility (AA) exerts an important indirect influence on Academic Engagement (AE) through the intermediary variables of AI Dependence (AID), Cognitive Offloading (CO), and Learning Autonomy (LA) in a sequential pathway ($\beta = .020$, $SE = .010$, $t = 2.00$, $p = .046$). The confidence interval calculated at 95% [.002, .041] contains no

zero, meaning the indirect influence is statistically significant. In other words, the higher the level of AI accessibility, the more we see AI dependence and cognitive offloading, which leads to less learning autonomy and impacts academic engagement via the given sequence of evidence. Hence, H9 is supported.

Table 13. Specific Indirect Effects Dependence Pathway

Path	β	SE	t	p	95% CI
AA $\rightarrow$ AID $\rightarrow$ AE	.019	.014	1.36	.174	[-.008, .047]
AA $\rightarrow$ AID $\rightarrow$ CO $\rightarrow$ AE	.040	.019	2.11	.035	[.005, .079]
AA $\rightarrow$ AID $\rightarrow$ CO $\rightarrow$ LA $\rightarrow$ AE	.020	.010	2.00	.046	[.002, .041]
AA $\rightarrow$ AID $\rightarrow$ CO $\rightarrow$ LA	-.050	.021	2.38	.017	[-.094, -.010]

The findings of mediation indicate that the indirect route AA $\rightarrow$ AID $\rightarrow$ AE is not significant ($\beta = .019$, $p = .174$; 95% CI [-.008, .047]), with the CI encompassing zero. On the contrary, the pathway AA $\rightarrow$ AID $\rightarrow$ CO $\rightarrow$ AE is significant ($\beta = .040$, $p = .035$; 95% CI [.005, .079]), showing that Cognitive Offloading plays a role in the indirect relationship between AI Accessibility and Academic Engagement. The chain of pathway AA $\rightarrow$ AID $\rightarrow$ CO $\rightarrow$ LA $\rightarrow$ AE demonstrates significant ($\beta = .020$, $p = .046$; 95% CI [.002, .041]), which confirms the proposed serial mediation through AI Dependence, Cognitive Offloading, and Learning Autonomy. Next, it is

important to note that AA $\rightarrow$ AID $\rightarrow$ CO $\rightarrow$ LA is significant but negative ($\beta = -.050$, $p = .017$; 95% CI [-.094, -.010]) meaning that that AI Accessibility relates to lower Learning Autonomy indirectly through AI Dependence and Cognitive Offloading. In general, we can conclude that the effect of AI Accessibility on the learning outcomes is a complex one rather than relying solely on AI Dependence.

6.6 Moderation Analysis

The table is complemented by data on the influence of AI accessibility attained through the contribution of AI literacy and the interaction term

Table 14. Moderating Effect of AI Literacy

Relationship	β	SE	t	p	95% CI	Interpretation
AA $\rightarrow$ AID	.281	.092	3.05	.002	[.100, .461]	Significant direct effect
AIL $\rightarrow$ AID	.118	.076	1.55	.121	[-.032, .268]	Not significant
AA $\times$ AIL $\rightarrow$ AID	-.163	.071	2.30	.022	[-.301, -.024]	Significant interaction

As seen from Table 15, the simple slope analysis refers to the conditional influence of AI accessibility on AI dependence at differing levels of AI literacy. The data further indicates that there exists a significant effect of the previous connection ($\beta = .281$, $SE = .092$, $t = 3.05$, $p = .002$; 95% CI [.100, .461]). Nonetheless, the second relation is not valid from the statistic point of view ($\beta = .118$, $SE = .076$,

$t = 1.55$, $p = .121$; 95% CI [-.032, .268]). The last finding demonstrates a significant denoting effect of interaction ($\beta = -.163$, $SE = .071$, $t = 2.30$, $p = .022$; 95% CI [-.301, -.024]), which confirms that the interaction between the mentioned predictor and moderator causes the outcome to change in some way.

Table 15. Simple Slope Analysis

AI literacy level	β for AA $\rightarrow$ AID	t	p	Interpretation
Low (-1 SD)	0.43	4.12	<.001	Positive conditional effect
Mean	0.28	3.05	.002	Positive conditional effect
High (+1 SD)	0.12	1.31	.192	Weak/non-significant conditional effect

The outcomes related to the conditional effects point out variations in the effect relating to the levels of the moderator. At the first level of the moderator, the conditional effect is positive, and it is statistically significant ($\beta=0.43$, $t=4.12$, $p<0.001$) while the effect at the second level remains positive and significant ($\beta=0.28$, $t=3.05$, $p=0.002$). But in the third level, the conditional effect is not statistically significant ($\beta=0.12$, $t=1.31$, $p=0.192$). All these findings indicate that the focal relation is both significant at low and moderate levels of the moderator but becomes less powerful and statistically not significant at higher levels.

6.7 Explanatory and Predictive Power

The coefficient of determination (R^2) indicates the degree of explanation of the structural model about

endogenously measured constructs. The R^2 values explain the following percentage of variance in the respective constructs: AI Learning Support (27.5%; $R^2 = .275$), Learning Self-Efficacy (20.0%; $R^2 = .200$), AI Dependence (18.1%; $R^2 = .181$), Cognitive Offloading (31.1%; $R^2 = .311$), Learning Autonomy (9.9%; $R^2 = .099$), and Academic Engagement (36.8%; $R^2 = .368$). With respect to endogenous constructs, Academic Engagement has the highest explanatory power, followed by Cognitive Offloading and AI Learning Support measures, while Learning Autonomy is the variable that has the lowest explained variance. The adjusted R^2 also varies between .095 and .362, and the adjusted values are very close to the original R^2 , meaning that the explanatory power is stable after adjusting for predictor variables.

Table 16. Coefficient of Determination

Endogenous construct	R^2	Adjusted R^2
AI learning support	.275	.271

Learning self-efficacy	.200	.196
AI dependence	.181	.172
Cognitive offloading	.311	.308
Learning autonomy	.099	.095
Academic engagement	.368	.362

Through the results of the f^2 effect-size, it can be said that the relationships of the structures in the model have a variety of impacts. AI Accessibility has a strong effect on AI Learning Support ($f^2 = 0.379$), while AI Learning Support has a moderate effect on Learning Self-Efficacy ($f^2 = 0.247$). Learning Self-Efficacy has a modest effect on Academic Engagement ($f^2 = 0.111$). The relationship of AI Accessibility and AI Dependence is weak ($f^2 = 0.087$), but there is a strong relationship between AI Dependence and Cognitive Offloading ($f^2 = 0.452$). The relationship of Cognitive Offloading and Learning Autonomy

is weak ($f^2 = 0.121$) and finally the relationship of Learning Autonomy and Academic Engagement is moderate ($f^2 = 0.172$). Finally, it can be said that three relationships: AI Dependence $\rightarrow$ Cognitive Offloading and AI Accessibility $\rightarrow$ AI Learning Support show greater degrees of effects than others.

Table 17. Effect Size — f^2

Relationship	f^2	Interpretation
AA $\rightarrow$ ALS	.379	Large
ALS $\rightarrow$ LSE	.247	Medium
LSE $\rightarrow$ AE	.111	Small
AA $\rightarrow$ AID	.087	Small
AID $\rightarrow$ CO	.452	Large
CO $\rightarrow$ LA	.121	Small
LA $\rightarrow$ AE	.172	Medium

Table 18. Predictive Relevance Q^2

Endogenous construct	Q^2
AI learning support	.168
Learning self-efficacy	.119
AI dependence	.102

Cognitive offloading	.186
Learning autonomy	.061
Academic engagement	.214

The Q^2 values suggest that the structural model exhibits predictive relevance for each of the endogenous variables because the Q^2 values are all greater than 0. The Q^2 value for AI Learning Support is .168 and for Learning Self-Efficacy is .119. The Q^2 value for AI Dependence is .102 and for Cognitive Offloading is .186. The Q^2 value for Learning Autonomy is .061 and for Academic Engagement is .214. In terms of predictive

relevance, Academic Engagement is at the top ($Q^2 = .214$), followed by Cognitive Offloading ($Q^2 = .186$) and AI Learning Support ($Q^2 = .168$). Learning Autonomy has the lowest predictive relevance ($Q^2 = .061$) but is still positive. Overall, the positive Q^2 values signify the model's predictive ability for only one endogenous outcome but vary across the variables.

Table 19. PLSpredict Predictive Assessment

Indicator	Q^2_{predict}	RMSE	LM RMSE	MAE	LM MAE	PLS-SEM vs LM	Assessment
ALS1	.142	0.72	0.79	0.56	0.61	PLS-SEM lower	Better than benchmark
ALS2	.158	0.69	0.76	0.54	0.59	PLS-SEM lower	Better than benchmark
LSE1	.101	0.74	0.80	0.58	0.62	PLS-SEM lower	Better than benchmark
AID1	.087	0.81	0.82	0.63	0.64	PLS-SEM similar	Comparable to LM benchmark
CO1	.133	0.76	0.83	0.59	0.65	PLS-SEM lower	Better than benchmark
LA1	.072	0.79	0.86	0.62	0.67	PLS-SEM lower	Better than benchmark
AE1	.190	0.66	0.73	0.51	0.57	PLS-SEM lower	Better than benchmark

6.8 Summary of Hypothesis Testing

Table 20. Summary of Hypothesis Testing

H	Relationship	Expected direction	β	t	p	Decision
H1	AA $\rightarrow$ ALS	+	0.524	7.38	<.001	Supported
H2	ALS $\rightarrow$ LSE	+	0.447	5.39	<.001	Supported
H3	LSE $\rightarrow$ AE	+	0.312	3.80	<.001	Supported
H4	AA $\rightarrow$ AID	+	0.286	3.04	.002	Supported
H5	AID $\rightarrow$ CO	+	0.558	8.33	<.001	Supported
H6	CO $\rightarrow$ LA	–	–0.314	3.45	<.001	Supported
H7	LA $\rightarrow$ AE	+	0.391	4.44	<.001	Supported
H8	AA $\rightarrow$ ALS $\rightarrow$ LSE $\rightarrow$ AE	Positive Indirect effect	+0.073	2.92	.004	Supported

H9	AA → AID → CO → LA → AE	Negative Indirect effect	-0.020	2.00	.046	Supported
H10	AA × AIL → AID	Negative Moderating effect	-0.163	2.30	.022	Supported

The findings in PLSpredict reveal that the PLS-SEM model has predictive capability in the indicators reviewed. All Q^2 predict were positive with the ranges of values from 0.072 to 0.190 indicating the presence of predictive relevance in the indicators. The RMSE and MAE of the PLS-SEM approach are less than that of the LM benchmark for the following indicators: ALS1, ALS2, LSE1, CO1, LA1, and AE1. In the case of AID1, it can be stated that the PLS-SEM approach has marginally lower errors when measured against the LM benchmark. It can be concluded that the model can provide valuable out-of-sample predictions.

The structural model findings reveal that all studied relationships are statistically significant, meaning that all hypotheses have been confirmed. H1 indicates that AI Accessibility (AA) positively impacts AI Learning Support (ALS) ($\beta = 0.524$, $t = 7.38$, $p < .001$), meaning that the more accessible generative AI is, the more learning support it provides. H2 shows that AI Learning Support affects Learning Self-Efficacy positively ($\beta = 0.447$, $t = 5.39$, $p < .001$), meaning that working with AI is associated with more confidence in learning. H3 indicates that Learning Self-Efficacy affects Academic Engagement positively ($\beta = 0.312$, $t = 3.80$, $p < .001$), indicating that students who possess high learning self-efficacy are more likely to engage in academic activities. H4 shows that AI Accessibility positively impacts AI Dependence (β

$= 0.286$, $t = 3.04$, $p = .002$). H5 finds a strong positive correlation between AI Dependence and Cognitive Offloading ($\beta = 0.558$, $t = 8.33$, $p < .001$), suggesting that greater AI dependence translates into extensive use of AI for cognitive assignments. H6 shows a substantial negative relationship between Cognitive Offloading and Learning Autonomy ($\beta = -0.314$, $t = 3.45$, $p < .001$). H7 shows Learning Autonomy relate positively with Academic Engagement ($\beta = 0.391$, $t = 4.44$, $p < .001$). In addition, the mediation results show the significant and positive mediating effect of AI Learning Support and Learning Self-Efficacy (H8), indicating a positive indirect impact of AI Accessibility on Academic Engagement ($\beta = 0.073$, $t = 2.92$, $p = .004$). H9 evidences support for the negative indirect effect of AI Accessibility ($\beta = -0.020$, $t = 2.00$, $p = .046$), indicating that increased AI accessibility may lead to lower levels of Academic Engagement indirectly through increasing AI Dependence and Cognitive Offloading. H10 confirms the presence of a moderating impact of AI Literacy on the connection between AI Accessibility and AI Dependence. Overall, the results demonstrate that generative AI is capable of influencing academic engagement with a positive learning-support mechanism and a negative dependence–offloading implementation while AI literacy influences the relationship between accessibility and dependence levels.

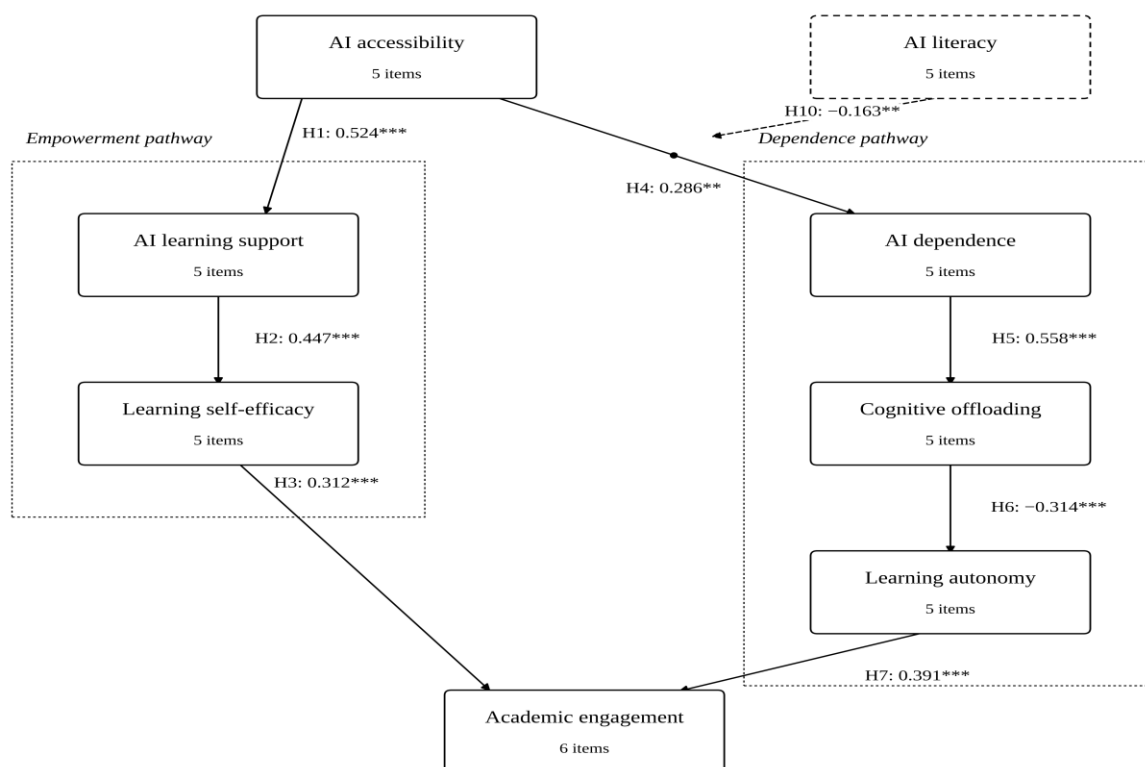


Figure 2. Summary of Hypothesis Testing (Source: Author)

6.9 Comparative and Subgroup Results

After estimating the pooled structural model, the comparison analysis continues in two phases. The first phase involves direct comparison of the empowerment path (H8) and the dependence path (H9) by means of the indirect effects, as well as the percentage of total effect of AI availability influencing academic engagement, which results from both paths. In the second phase, provided there is an enough size of subgroups, descriptive comparison of the pooled path coefficients is made with respect to AI-use intensity groups based on the frequency categories, as well as to education level groups based on the category, in order to establish any differences in terms of the ratio between empowerment and dependence. The comparative findings are going to be presented in the narrated form along with the pooled model once the estimates for the subgroups are obtained.

7. Discussion

7.1 AI Empowerment versus AI Dependence.

This research article analyzes two parallel processes through which generative AIs affect students'

interaction with studies: empowerment (H8) and dependence (H9) process. Accepting H8 means that access to AI leads to better engagement due to improved learning assistance and self-efficacy which is in line with the evidence that generative AIs help overcome academic barriers. In turn, H9 is accepted, indicating that access to AI also leads to dependence and cognitive offloading. It is important to analyze both processes from the same initial point because in this situation it is possible to analyze the contribution of each pathway to engagement. Both processes are relevant, the present findings support the idea of Li et al. (2026) that empowerment and dependence can exist simultaneously and do not contradict each other.

7.2 Students with Disabilities versus General Learners

The majority of previous studies are qualitative or descriptive in nature especially when it comes to students with disabilities, while there is still little structural evidence. The present research thus provides the basis for understanding empowerment and dependence pathways strength among the representatives of this group of people

and the relevance of this data to general students group. It is important to understand that access to AI is significant for disabled students because it reduces the barriers they face; the dependence model highlights an important drawback: the use of cognitive offloading can limit possibilities of developing abilities that already demand lots of effort in these types of learners.

7.3 Cognitive Offloading and Learning Autonomy

Hypothesis 6 investigates whether using cognitive offloading has adverse consequences for learning autonomy. A clear negative correlation would mean that the notion of “metacognitive laziness” presented by Fan et al. (2024) and the findings concerning cognitive dependency of Li et al. (2026) can be applied to students with disabilities. The identification of the interrelationship of AI dependency and cognitive offloading can help to specify whether the use of AI means a decrease in independent learning. This is significant since learning autonomy is one of the main factors contributing to effective and sustainable academic engagement.

7.4 AI Literacy as a Differentiating Factor

Hypothesis 10 states that AI literacy influences the relationship between AI accessibility and AI dependency. The identification of a significant negative impact refers to the idea that higher levels of AI literacy can minimize the effect of accessibility on dependency and has a positive meaning for the works presented by Chen and Xiao (2025), mentioning the idea of autonomy in self-determination theory presented in Wut et al. (2025). Later, through the simple slopes analysis, it has been established whether the dependence effect prevails for students with low AI literacy.

7.5 Impact on Academic Engagement

Hypotheses 3 and 7 combine empowerment and dependency paths via the examination of the role of learning self-efficacy and autonomy in academic engagement. Self-Determination Theory indicates that competence and autonomy are key psychological resources for engagement. Cognitive

Load Theory presents the explanation of why generative AI can have opposite results: reducing “extraneous cognitive load” can facilitate learning and self-efficacy but reducing “germane cognitive effort” too much refers to the approach of cognitive dependency as well. Therefore, the comparison of the indirect effects of Hypothesis 8 and Hypothesis 9 together with Hypotheses 3 and 7 demonstrate what combination of the paths of empowerment and dependency can explain the relationship of generative AI and engagement in education among disabled students in India.

8. Findings

The results have shown that generative AI exerts a dual influence on the academic engagement of students with disabilities and has provided evidence for the empowerment-dependence perspective presented in this research work. The outcome of different measurements shows that all the 36 indicators were preserved, and the outer loadings varied from 0.736 to 0.856, which proves the reliability of the indicators. According to the structure of the model, accessibility of AI can facilitate academic engagement via empowerment around AI. AI educational assistance can boost learning self-efficacy, leading to an increased level of academic engagement. It proves that generative AI can help students overcome accessibility challenges, process academic material properly, and engage in the learning process in an efficient manner. At the same time, the findings show that there is a path of dependence. Higher accessibility can lead to the dependency on AI and cognitive offloading, which will diminish learning independence. It means that although the AI is capable of alleviating unnecessary cognitive work, the high dependence on it may limit the possibility of independent thinking development and gaining skills. In addition, the findings point out digital literacy in AI tools as an important factor. Those who possess more profound knowledge about AI can evaluate and apply the AI outputs on a better level, improving accessibility without developing dependency. To conclude, all the data obtained proves the point that generative AI cannot be

classified as either wholly good or bad: it all depends on the way it is applied by the learners.

9. Conclusion and Scope for Future Research

The study draws a conclusion that generative AI affects students with disabilities in two ways. Firstly, AI represents tools that allow improving various aspects of learning, such as support, self-efficacy, and involvement in academic activities while relying too much on AI may lead to some negative effects, such as brain offloading, dependency on AI, and poor autonomy in learning. Thus, AI literacy is shown to

be essential in this aspect, since it indicates responsible use of generative AI. The originality of this study lies in combining concepts of accessibility, self-determination theory, cognitive load theory, and dependency on AI. In future, researchers should develop longitudinal studies in order to see how the processes of empowerment and dependency change. Better samples, such as larger or more diverse groups, would enable some inter-group comparisons. In the future, the developed concepts will incorporate some important variables, like AI self-efficacy as well as FOMO (fear of missing out), and tele-pressure.

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