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Advancing AI in Higher Education: Responsible Practices, Leader's Cognitive Involvement, and Adoption Synergy

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ABSTRACT:

The rapid growth of artificial intelligence (AI) is reshaping higher education. This study examines AI's potential in Indian universities, considering stakeholder views and leadership roles. Key questions explored include how responsible AI affects AI adoption and the role of leadership cognitive engagement. It is a quantitative research, and after running CFA using AMOS, SPSS was utilised for mediation analysis. The study concludes that responsible AI practices and leadership engagement are crucial for effective AI adoption. AI's role in education's future hinges on ethical practices and proactive leadership. Recognising the mediating role of the leader's cognitive engagement highlights the need of leadership development courses that increase leaders' knowledge of responsible AI and its implications. Such courses/ training can prepare top management of these HEIs to advocate for the use of AI technology while keeping ethical considerations in mind.

Keywords: Responsible artificial intelligence, higher educational institutions, AI adoption, responsible AI, leadership cognitive engagement

INTRODUCTION

The landscape of higher education is changing dramatically as a result of fast advances in artificial intelligence (AI) and the expanding capabilities of intelligent machines (Guo et al. 2020). This transformation brings both enormous potential and significant problems, transforming the way higher education institutions approach teaching and learning (Kumar et al. 2020). The incorporation of artificial intelligence has the potential to transform not just teaching approaches, but also the general administration and organisational structure of these institutions.

Artificial intelligence spans a wide range of functions, including visual perception, speech recognition, data-driven decision-making and language translation, and is characterised by computers and robots replicating human cognitive processes (Su and Yang, 2022). AI has invaded all facets of contemporary life, appearing as intelligent sensors and interactive virtual companions with the ability to mimic human-like thinking and behaviour (Krishnaveni and Meenakumari, 2010).

Because of the rapid advances in AI technology, the field of higher education has seen substantial upheavals (Garcia et al. 2021). AI-powered learning experiences are fostering a symbiotic relationship between learners and educators by doing activities that previously

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required human logical thinking and comprehension. However, although AI offers the potential of a transformational future, it also carries with it a slew of technical issues that require careful analysis and prudent deployment.

The modern world has evolved from a period characterised by traditional living circumstances to one characterised by innovation and inventiveness. This paradigm shift has been driven by technology advances, notably the internet, which has fundamentally transformed attitudes on education and work. In recent years, the notion of "AI technology" has arisen as a critical force among these technical breakthroughs.

The current study aims to identify possible AI adoption scenarios in the context of higher education and communicate these options to policymakers in the sector. It investigates the possible influence of AI on higher education and analyses the readiness of Indian higher education institutions to adopt and successfully utilise these disruptive technologies. Institutions that engage on the road of integrating AI into academics are likely to confront multiple problems that demand detailed review and strategic navigation.

This study aims to answer three critical issues about the use of AI in higher education in India:

- How will responsible AI applications impact stakeholders' perspectives and attitudes towards artificial intelligence adoption in Indian higher education institutions?

- It also explores the role of leader cognitive engagement in facilitating successful AI adoption in higher educational institution.

Our study intends to give significant insights into the consequences and challenges related with the integration of AI technology inside higher education, with a special focus on rising economies such as India, by explaining these queries. The findings of this study will help higher education administrators, policymakers, and stakeholders navigate the complex landscape of AI adoption and its possible implications for the future of education.

The need of investigating the interaction between AI technology and education is highlighted by the enormous societal upheavals catalysed by the COVID-19 epidemic, which have highlighted the importance of digital technology and its role in education. This investigation of the dynamic interaction between AI and education intends to shed light on these complex processes and contribute to the development of a more educated and nuanced discourse in the subject.

The rise of AI has been heralded as a cure for a variety of educational difficulties, but with scant empirical proof. This underscores the importance of doing a thorough evaluation of the goals, modalities, stakeholders, and deployment strategies around AI in education.

While AI and education (AIED) differences are numerous, they include areas such as "teaching with AI," "learning about AI," "teaching AI," and "preparing for AI." Each area

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covers a distinct aspect of AI's impact on education, ranging from using AI technologies to improve learning to promoting AI literacy among educators and students (Kim et al. 2020).

The expansion of AI technology has resulted in the creation of massive volumes of data, which is referred to as AIED. Interactions between learners and AI systems create a massive amount of data, providing new insights into learning behaviours and preferences (Guan et al. 2020).

Parallel to this, the relationship between public education and private enterprise is changing, with far-reaching repercussions for markets, cultures, nations, and individual students. As multinational businesses gain influence over educational objectives and goods, issues concerning their impact on institutional practises and policy-making arise (Tong et al. 2019).

As artificial intelligence continues to pervade many fields such as mobile apps, healthcare systems, and web services, its disruptive potential in education is similarly deep. This research aims to delve into the many facets of AI-assisted education, unravelling its promises and complexity while also contributing to the continued progress of AI-based pedagogy (Hannan and Liu, 2021). Because the area of AI-based teaching is still in its early stages, the goal of this research is to give insights that can drive the creation of complete AI-integrated education systems, with educators actively involved in their development.

This study analyses the promise and challenges of AI in teaching practise as shown by research to address these knowledge gaps. Because the field of AI-based teaching is still in its early phases of development, this research can help in the development of full AI-based education systems that allow instructors to participate in the design process.

The next portions of the study are organised as follows: section II discusses the literature review, while sections III and IV cover the methodology and data analysis, respectively. Section-V of the paper contains the discussion, while Section-VI contains the concluding remarks.

REVIEW OF LITERATURE

Artificial intelligence (AI) has received a lot of interest in the setting of higher education institutions (HEIs), especially for its potential to improve the learning environment and educational practises. Wogu et al. (2018) explored the consequences of AI and artificial instructors for learners in the context of the twenty-first-century education industry. In their review study, Wogu et al. (2018) emphasised the possibility for AI to progressively take over human employment and the significance of evaluating ethical and performance concerns in AI integration. Zawacki-Richter et al. (2019) undertook a comprehensive evaluation of artificial intelligence (AI) applications in higher education. Their research emphasised the importance of AI in improving educational elements and underlined the necessity for greater research on educational consequences.

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Bates et al. (2020) investigated AI's transformational potential in higher education. Their review study emphasised AI's potential to transform education and advocated for the use of contemporary teaching techniques and technology. Chen et al. (2020) did a thorough review of the rise of artificial intelligence in education. Their findings revealed limitations in the application and theoretical elements of artificial intelligence adoption in educational settings. The study recommended concentrating on integrating AI in physical classroom settings, analysing student responses in intelligent tutoring systems, and implementing sophisticated deep learning algorithms.

Chiu and Chai (2020) investigated sustainable curriculum development for AI education in HEI from the standpoint of self-determination theory. They emphasised the need of long-term curriculum development that includes AI technology and corresponds with students' self-determined learning goals. Qasem et al. (2020) used a multi-analytical method to investigate the factors of cloud computing uptake in higher education institutions. Their research identified characteristics that influence cloud computing adoption and emphasised the importance of technological readiness and other associated criteria.

Ahmad et al. (2021) examined the function of AI in education and emphasised the significance of using current teaching techniques and technology to improve the educational experience. Damerji and Salimi (2021) explored the role of use perceptions in moderating the technological readiness and acceptance of AI in accounting. They used an online questionnaire to investigate how consumers' views impact AI adoption in accounting. Hwang and Tu (2021) conducted a thorough evaluation of artificial intelligence's functions and research trends in mathematics education. Their research examined artificial intelligence's contributions to mathematics education research, identifying several application areas and achievements.

González-Calatayud et al. (2021) undertook a thorough evaluation of the function of artificial intelligence in student assessment. They reviewed the benefits and drawbacks of employing AI for educational evaluation and emphasised the need of teacher training and educational research. Kuleto et al. (2021) investigated the prospects and constraints of AI and machine learning in HEI. Their empirical study, which included Serbian students, highlighted the usefulness of AI and machine learning technologies in supporting collaborative learning and enhancing research settings. Leoste et al. (2021) investigated the potential integration of developing technologies in higher education, such as robots and AI. Their empirical study focused on instructors' and students' opinions of the possible influence of developing technology on education. Li et al. (2021) performed an empirical research on AI, machine learning, and extended reality deployment in higher education institutions. They emphasised the relevance of AI and machine learning technology in the development of students' talents in higher education.

Bucea-Manea-oniş et al. (2022) did an empirical research in Romania and Serbia to investigate the influence of AI on learning environments in higher education institutions.

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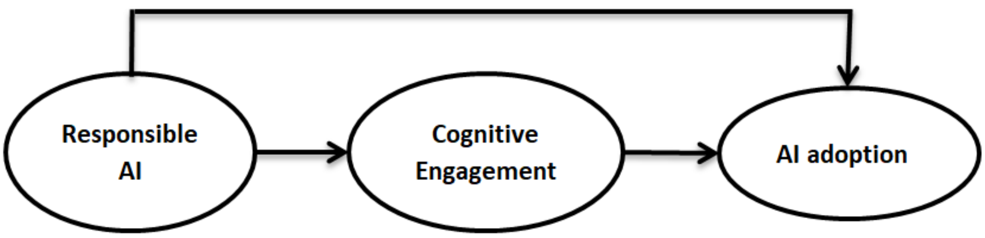
They used quantitative analysis and multiple-choice questions to assess the use of AI technologies in instructional initiatives. The study discovered that AI-driven applications had a favourable effect on activities taken in higher education institutions. Roy et al. (2022) explored the desire to use AI-based robots to educate students at colleges. They used a questionnaire to analyse professor and student attitudes on AI adoption. The findings revealed that AI, particularly natural language processing-enabled intelligent tutor systems, can improve several areas of education, including self-reflection and decision-making skills.

These studies add to a complete knowledge of AI's function in higher education institutions, giving light on its possible advantages, problems, and consequences for teaching, learning, and organisational decision-making. The findings emphasise the significance of responsible AI adoption, cognitive engagement, and technological preparedness in influencing higher education's future. The following theory has been developed based on the aforementioned literature:

H1: Responsible AI has a positive effect on AI Adoption.

H2: The effect of Responsible AI on AI Adoption is mediated by Leader's Cognitive Engagement.

2.1 Conceptual Framework



METHODOLOGY

3.1 Research Design

The study was quantitative in nature and was done on higher educational institutions in North India. The unit of analysis was the faculty and administration, and data was collected using structured questionnaires based on a previously created measuring scale. This study uses a cross-sectional method to investigate how responsible AI practises influence AI uptake in higher education in North India. It also investigates the importance of leader cognitive involvement in promoting successful AI integration.

3.2. Data Collection

Structure questionnaires were used to obtain data. To be more specific, in this study, purposive sampling methods were used to choose participants who fit specific conditions related to the subject matter of the research or characteristics of the population under investigation (Bryman, 2016, p. 251). When the researcher aims to focus on a certain group

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or subgroup that is most likely to produce in-depth and important information, purposeful sampling is suitable and recommended (Patton, 2002; Guest et al., 2006). Three criteria were established for the selection of the sample HEI: first, the HEI must be located in north India; second, it must be a private institution; and third, the institution must have been in operation for at least six years. The questionnaires were delivered by Google form and direct email. Respondents included university faculty and administration. A total of 650 questionnaires were distributed to participants, and 398 were returned after one month; after verifying for missing and incomplete information, only 387 questionnaires were completed and usable for the analysis. Eleven surveys were deleted because they were incomplete and hence unusable for further investigation. The returned rate of the questionnaire was 61.23%. Prior to distribution, the questionnaires were reviewed by professionals and academics, and their criticism was suitably addressed, therefore ensuring the validity of study instruments. Before being evaluated, these experts were briefed about the study's goal and scope. The questionnaires for this study are divided into two portions. Section 1 comprises demographic factors such as age, education, job experience, and so on, whereas Section 2 contains items utilised for study constructions.

3.3. Variable's Measurement

This study's variables were all computed using a previously used and created scale. The validity, reliability and the accuracy of measures were tested using a pilot test using questionnaires. The items were measured using a 5-point Likert scale, with strongly agree = 1 and strongly disagree = 5. The variables' measurements are explained more below.

3.3.1. Responsible AI

For the measurement of Responsible AI, we used standardized scale adapted from (Kumar et al., 2021).

3.3.2. Cognitive engagement

Our study used scales for the measurement of leader's cognitive engagement, which was adapted from (Graffigana et al., 2015)

3.3.3. AI Adoption

The AI adoption is measured through adapted from (Hatlevik, and Bjarnø, 2021).

3.4 Statistical Analysis

The conclusions were determined using a variety of statistical methodologies. The data was initially assessed for common method bias (CMB), which can be an issue in research using self-report measures (Nunnally, 1978). CMB was analysed using the SPSS software's EFA and the Harman single factor test. Before reviewing the structural model, confirmatory factor analysis (CFA) was utilised to analyse the study model's accuracy, reliability, and validity. The convergent validity of the exogenous and endogenous constructs was tested using AVE

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and standardised loadings of the constructs (Hair et al., 2010). Bagozzi et al. (1991) discovered that an AVE value more than 0.5 indicates substantial convergent validity, but Kline (2005) discovered that items with a standardised loading greater than 0.6 are more likely to be valid.

Hair et al. (2010) introduced discriminant validity tests to determine how much one component in the measurement model differed from others. As a discriminant validity requirement, the square root of AVE should be greater than the inter-construct correlation coefficients, indicating that the components are not strongly related. The structural model connection was employed in the study to assess the significance of the individual path as well as the model's exploratory potential. Hair et al. (2019) proposed utilising the route coefficient (β) to assess structural model strength. The standardised value indicates the strength of the proposed link (Weston & Gore, 2006).

3.5 Quality checks

A variety of preliminary checks were carried out prior to final analysis. We investigated non-response bias by comparing the mean difference between early (n=50) and late (n=50) respondents, but found no significant difference, demonstrating the absence of such bias. The final sample of 387 was used for further investigation. We were able to rule out the potential of CMB, which had a variance for a single factor of just 24.46%, which was less than the threshold amount.

DATA ANALYSIS

4.1 Sample statistics

Table 1: Sample statistics

Demographic Variable	Categories	Frequency	Percentage
Gender	Male	184	47.55
	Female	203	52.45
Age (in Years)	20-30	139	35.92
	31-40	149	38.50
	41-50	85	21.96
	51 and above	14	3.62
Marital Status	Single	97	25.06
	Married	290	74.94
Working Experience (Years)	Less than 1	31	8.01
	1-5 Years	141	36.43
	6-10 Years	118	30.49
	More than 10	97	25.06

Source: Authors' Computation

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Table 1 displays the profiles of survey respondents. Men made up 47.55% of the participants, while women made up 52.45%. The age range with the largest representation (38.50%) was 31 to 40. The marital status of the participant was also included in the percentage and frequency distributions. According to the results, 74.94% of the participants were married, while 25.06% of the participants were single. Following our examination of the participants, we determined that 7.28% had less than one year of experience, while 36.43% had between one and five years of experience. As a result, 30.49% of employees reported working at educational institutions for 6 to 10 years, while 25.06% reported working there for more than 10 years.

4.3 Measurement model

The measurement model provided a goodness of fit values for different indices: chi-square (406) = 1201.99, $p < 0.05$, χ^2/df = 2.98, CFI = 0.902, IFI = 0.906, TLI = 0.909, RMSEA = 0.065. We used Kline's (2005) recommendation for convergent validity, and as a result, all item loadings for all sub-constructs were higher than the suggested threshold value of 0.60, ranging from 0.611 to 0.975. Further, the critical ratios for every scale item were also all over 1.96. Thus, these findings exhibit convergent validity. The constructs' composite reliabilities (CRs), which vary from 0.793 to 0.906, show strong internal consistency.

Table 2: Measurement Model

			Estimate	S.E.	C.R.	p-value
DTA4	<---	Responsible AI	0.973			
DTA3	<---	Responsible AI	0.872	0.027	38.919	***
DTA2	<---	Responsible AI	0.655	0.04	19.629	***
DTA1	<---	Responsible AI	0.92	0.018	48.913	***
IES4	<---	Responsible AI	0.648	0.058	12.186	***
IES3	<---	Responsible AI	0.972	0.055	26.272	***
IES2	<---	Responsible AI	0.611	0.046	12.996	***
IES1	<---	Responsible AI	0.839			
SES4	<---	Responsible AI	0.9			
SES3	<---	Responsible AI	0.619	0.031	14.448	***
SES2	<---	Responsible AI	0.887	0.02	34.79	***
SES1	<---	Responsible AI	0.963	0.017	43.854	***
PRR1	<---	Responsible AI	0.847			
PRR2	<---	Responsible AI	0.956	0.058	18.401	***
PRR3	<---	Responsible AI	0.869	0.02	42.137	***
PRR4	<---	Responsible AI	0.846	0.047	16.509	***
TRA1	<---	Responsible AI	0.957			

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TRA2	<---	Responsible AI	0.918	0.014	58.12	***
TRA3	<---	Responsible AI	0.957	0.012	69.872	***
TRA4	<---	Responsible AI	0.954	0.012	67.746	***
ALM1	<---	Responsible AI	0.706	0.026	21.585	***
ALM2	<---	Responsible AI	0.966	0.02	45.236	***
ALM3	<---	Responsible AI	0.718	0.026	22.234	***
ALM4	<---	Responsible AI	0.914			
CPR1	<---	Responsible AI	0.917			
CPR2	<---	Responsible AI	0.974	0.015	57.252	***
CPR3	<---	Responsible AI	0.975	0.015	57.626	***
CEG1	<---	Cognitive Engagement	0.684			
CEG2	<---	Cognitive Engagement	0.748	0.071	14.586	***
CEG3	<---	Cognitive Engagement	0.745	0.073	14.554	***
CEG4	<---	Cognitive Engagement	0.668	0.075	11.608	***
ADO1	<---	AI Adoption	0.812			
ADO2	<---	AI Adoption	0.798	0.046	20.64	***
ADO3	<---	AI Adoption	0.792	0.041	21.259	***
ADO4	<---	AI Adoption	0.726	0.045	18.084	***
ADO5	<---	AI Adoption	0.664	0.041	16.737	***

Source: Authors' Calculations

The square root of AVE values range from 0.721 to 0.778 (see Table 3) and are greater than the inter-item correlation coefficients values which signifies that the constructs are not highly correlated (Fornell & Larcker, 1981; Hair et al., 2010). Therefore, every requirement for discriminant validity has been met. The measurement model possesses good overall reliability and validity, and is ready for structural testing.

Table 3: Measures' discriminant validity.

Variable	ALM	DTA	IES	SES	PRR	TRA	CPR	CEG	ADO
ALM	**0.84**								
DTA	0.36	**0.87**							
IES	0.48	0.25	**0.75**						
SES	0.32	0.16	0.47	**0.84**					
PRR	0.47	0.23	0.27	0.1	**0.89**				
TRA	0.2	0.12	0.07	0.47	0.09	**0.96**			
CPR	0.4	0.1	0.08	0.08	0.15	0.01	**0.96**		
CEG	0.02	0.04	0.05	0.03	0.06	0.03	0.01	**0.7**	
ADO	0.11	0.11	0.2	0.17	0.04	0.1	0.03	0.61	**0.77**

Source: Authors' Calculations (Values in bold are the square root of the AVE.)

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4.4 Mediation test

In contrast to the multistep approach commonly employed to assess mediation, SPSS macro PROCESS (Hayes, 2013) is utilised in this study for simple mediation (Model 4). In the current study, Hayes' (2013) PROCESS macro was used to account for the leader's cognitive engagement's mediation function in the relationship between responsible AI and AI adoption.

4.4.1 Simple mediation analysis

Using simple mediation analysis, the hypothesis of the routes and causation from Responsible AI to AI adoption via Leader's cognitive engagement was investigated. Hayes (2013) PROCESS (Model 4) is employed to do this.

Table 4. Regression results from simple mediation

Model	Coeff.	se	t	p	LLCI	ULCI	Outcome
constant	2.583	0.150	15.617	0.000	2.358	2.990	CEG
EEG	0.251	0.027	9.281	0.000	0.268	0.416	CEG
constant	1.672	0.234	7.144	0.000	1.281	2.244	ADO
EEG	0.199	0.038	6.059	0.000	0.194	0.386	ADO
CEG	0.217	0.047	5.443	0.000	0.195	0.421	ADO
constant	2.527	0.186	13.272	0.000	2.232	3.004	ADO
RAI	0.312	0.035	8.885	0.000	0.312	0.493	ADO

Source: Authors' Calculations

Table 5. Sobel Test

Effect	se	Z-value	P-value (2-tailed)	Lower bound	Upper bound
0.102	0.014	4.624	0.000	0.055	0.168

Source: Authors' Calculations

Table 4 shows the outcomes of the mediation analysis for hypotheses 1 and 2. According to Table 4, RAI has a significant influence on CEG (β = 0.251 while p-value β = 0.000). Furthermore, the findings show that RAI has a substantial influence on ADO (β = 0.312, p-value β = 0.000). Similarly, the data demonstrate that CEG has a statistically significant influence on criteria ADO (β = 0.21.7 while p-value = 0.000) and that RAI has a substantial effect on criterion i.e. ADO in the presence of CEG (β = 0.199 while p-value = 0.000). According to the study's findings, CEG partially mediates the action of RAI on ADO. The confidence intervals for the lower and upper levels do not contain a zero. Table 5 displays the results of the Sobel test. The table clearly illustrates that the effect size is more than zero and the p-value is significant, indicating that mediation between predictor and criteria occurs. As

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a result, CEG appears to be mediating the action of RAI on ADO. As a result, hypotheses H1 and H2 are accepted.

DISCUSSION

The purpose of this study was to look at the complex interaction between responsible AI, Leader cognitive engagement, and AI adoption in higher education institutions. The study hypotheses were developed in order to provide insight on the direct and indirect impacts of responsible AI on AI adoption via the intermediate function of Leader's cognitive involvement. The findings of the study give important insights into the crucial aspects that determine the effective application of AI technology in educational settings.

Hypothesis 1 (H1): Responsible AI and AI Adoption Relationship:

The first hypothesis, H1, proposed a positive association between responsible AI and AI adoption. This finding is consistent with the wider debate over the ethical application of AI technologies (Wogu et al., 2018; Zawacki-Richter et al., 2019). As higher education institutions attempt to incorporate AI into many facets of their operations, responsible AI use becomes increasingly important. Considerations of justice, transparency, accountability, and ethical decision-making in AI systems are all part of responsible AI. The favourable association discovered between responsible AI and AI adoption emphasises the need of connecting technology progress with ethical issues. Institutions that prioritise responsible AI are more likely to see higher levels of AI adoption, since stakeholders appreciate ethical technology integration.

Hypothesis 2 (H2): Mediating Role of Leader's Cognitive Engagement:

The second hypothesis, H2, claimed that Leader's cognitive involvement mediates the influence of responsible AI on AI adoption. According to this mediation, responsible AI influences Leaders' cognitive engagement, which in turn influences AI adoption. This finding highlights the importance of leaders in creating organisational culture and decision-making processes linked to AI deployment. Leaders that participate intellectually in ethical AI practises are more positioned to appreciate its benefits, solve possible problems, and build a climate conducive to effective AI integration. The mediating function of the Leader's cognitive involvement contributes to a more sophisticated understanding of the mechanisms by which responsible AI practises cascade down to influence AI adoption at the institutional level.

CONCLUSION

In conclusion, the current study's findings give convincing support for both hypotheses, confirming the positive association between responsible AI and AI adoption while emphasising the importance of Leader's cognitive involvement as a mediator. These findings add to the increasing body of information on AI implementation in higher education

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institutions and highlight the interdependence of ethical issues and leadership participation in this environment. Fostering responsible AI practises and cultivating cognitive involvement among leaders will be critical in attaining effective and ethical AI integration as institutions continue to adopt AI technology.

6.1 Implications, Limitations and Future Scope

The findings of the study have significant significance for higher education institutions attempting to negotiate the challenges of AI deployment. Institutions may provide the groundwork for ethical and sustainable technology integration by prioritising responsible AI practises. Recognising the mediating function of the leader's cognitive involvement also underscores the need for leadership development programmes that improve leaders' awareness of responsible AI and its ramifications. Such programmes can equip executives to advocate for the inclusion of AI technology while keeping ethical concerns at the forefront.

While this study has contributed to our knowledge of the links between responsible AI, Leader cognitive engagement, and AI adoption in higher education, certain limitations should be noted. The uniqueness of the sample may restrict generalizability, and the cross-sectional design precludes clear causal findings. To overcome these limitations, future study might benefit from using a longitudinal research approach. The possibility of self-reporting bias suggests the need for more objective measurements.

Future research might improve on this work by using qualitative approaches for nuanced insights, adopting longitudinal designs for temporal clarity, and investigating cross-cultural differences. Intervention research might provide practical techniques for increasing Leader cognitive engagement. Incorporating other viewpoints, such as those of students and other stakeholders, and building specialised ethical frameworks will help us better understand responsible AI inclusion in higher education. Addressing these limits and exploring these future possibilities will help us better understand the impact of responsible AI on AI adoption.

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