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Generative AI and Cognitive Sustainability Among Nigerian University Learners: A Socio-Materiality Framework

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Abstract

This study proposes a Perceived Cognitive Sustainability Socio-material Framework (PCSSF), grounded in socio-materiality theory, to explain how the entanglement between learners and GenAI tools produces "hybrid minds," which are associated with perceived cognitive offloading and, subsequently, perceived cognitive decline. The framework further incorporates institutional governance strategies as a mediating mechanism that helps reduce cognitive risks and support cognitive sustainability. The model was tested using covariance-based structural equation modeling (CB-SEM) on survey data from 420 students and researchers across higher educational institutions in Nigeria. Results indicate acceptable measurement and structural model fits, with statistically significant paths supporting six of the seven hypothesized relationships: socio-material entanglement was associated with hybrid mind/intelligence formation, which in turn was linked to perceived cognitive offloading and subsequent perceived cognitive decline. Institutional governance partially mediated the relationship between perceived cognitive offloading and perceived cognitive sustainability, but did not mediate the link between perceived cognitive offloading and perceived cognitive decline. Theoretically, this study reframes GenAI-induced cognitive change as an emergent socio-material phenomenon rather than a purely technological or human issue; conceptually, it positions learners and GenAI as co-learning entities; and practically, it offers institutions a governance-based framework to sustain learners' cognitive autonomy. Finally, the findings suggest that GenAI adoption in higher education should augment rather than replace human cognitive effort.

Keywords: generative AI, education, socio-materiality theory, cognitive sustainability

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1. Introduction

The emergence of Generative Artificial Intelligence (GenAI) technologies, including ChatGPT, DeepSeek, Copilot, Claude, and Gemini, is reshaping educational practices by enabling real-time interaction, knowledge synthesis, and creative learning through access to vast digital datasets (Chedrawi & Haddad, 2022). These technologies challenge teacher-centered models by introducing intelligent AI agents that continuously mediate learning processes as conversational assistants, adaptive support systems, and knowledge-generation tools, transforming the roles of educators, learners, and information resources within educational environments (Lodge & Loble, 2026).

In Nigerian higher educational institutions, where challenges such as large class sizes, limited academic resources, uneven digital infrastructure, and pressure for academic productivity exist, the growing GenAI adoption may create a paradox: learners assume GenAI democratizes access to intellectual resources, yet it also helps them bypass cognitive scaffolding processes associated with frameworks such as Bloom's taxonomy and Dewey's reflective learning theory (Peters & Olojede, 2025). This scenario amplifies cognitive offloading, as GenAI becomes the infrastructure that drives active learning and access to knowledge in a resource-constrained environment.

GenAI adoption in learning tasks has produced hybrid minds, intensifying debates between techno-optimistic and techno-pessimistic camps in higher education regarding its impact on human cognition (Yan et al., 2025). Amid this debate, growing empirical evidence shows that learners' over-reliance on GenAI models can undermine the cognitive effort required for critical, reflective thinking and problem-solving (Macnamara et al., 2024; Zhai et al., 2024); enabling potential for cognitive rot (Walther, 2025), short-term performance paradox for learners but harmful long-term metacognitive impairment (Lodge & Loble, 2026). These risks raise fears of producing a generation of learners unable to sustain academic achievement or adapt to workplace demands without technological support (Carmon, et al. 2027).

Previous studies have mainly examined the benefits and risks of generative AI tools in academia (Adesiji, 2024; Dwivedi et al., 2023), positive effects of GenAI tools in enhanced personalized guidance (Yan et al., 2025). However, research on GenAI-induced cognitive decline and how to sustain cognitive autonomy remains scarce (Bodislav & Georgescu, 2025; Lodge & Loble, 2026). A study by Dron (2023) highlighted the lack of research connecting GenAI-mediated learning with relevant theories of cognitive development in education. Likewise, Onunga (2025) found that GenAI overuse is compounded in developing countries like Nigeria, where

educational institutions are AI-ready but lack an AI maturity framework to address fragmented AI policy and governance for inclusive, sustainable AI adoption.

This study goes beyond the technological affordance of GenAI in education to explore what it means to learn in a GenAI-mediated environment where cognitive abilities and intelligence are contested (Yan et al., 2025), and proposes a framework for socio-material theoretically grounded human-GenAI co-creation, and for sustaining learners' cognitive abilities while they use GenAI tools for learning (Gerlich, 2025).

This study presents a novelty by adopting a combination of theoretically grounded framework to integrate socio-materiality with institutional governance on how GenAI and human adaptation has created a new learning paradigm, and how cognitive abilities can be sustained in educational learning environment.

To address these issues, this study identifies scholarly contributions guided by these questions:

- RQ1: How does human – generative AI socio-material alignment produce hybrid forms of cognition?
- RQ2: How does the emergence of hybrid cognition affect learner's cognition?
- RQ3: What mechanism regulates the effects of learners' hybrid cognition on learning?
- RQ4: What framework can help sustain the effect of GenAI on learners' cognitive abilities?

The paper is hereafter structured as follows: Section 2 reviews related literature and hypotheses development, section 3 presents the methodology, while section 4 present the results, section 5 discusses the results of the study, and section 6 concludes the study and makes recommendations.

2. Literature Review

The cognitive implications of GenAI in learning present three major directions regarding GenAI use in higher education: 1) understanding cognitive offloading and implications posed by GenAI, 2) understanding the theoretical basis for explaining the new phenomenon, and 3) a framework and hypotheses to be tested in empirical studies.

2.1. Cognitive Offloading and Implications in Learning

The fields of cognitive neuroscience, education, and information systems have started to uncover the nuances of how digital technology impacts brain functions (Westerbeek, 2026). Evidence is beginning to emerge that technological adoption, such as generative AI, can impact

learners' cognitive abilities. The new trend associated with the adoption of generative AI is that learners have inadvertently started to minimizing the exercise of cognitive muscles and over-rely on AI agents, and this has received different interpretations in literature, such as agency decay (Walther, 2025), brain rot (Yousef et al., 2025), cognitive offloading (Gerlich, 2025), and skill decay (Macnamara et al., 2024), and generative AI–induced cognitive atrophy (Westerbeek, 2026). While cognitive offloading is usually technologically – motivated, agency decay, brain rot, skill decay, and cognitive atrophy, most times extend beyond technological causes.

Walther (2025) explained that the routine brain activities usually create neural pathways in the biological neural networks, and those neurons that aren't regularly used weaken through a process called synaptic pruning. This scenario underscores what happens when the human brain is routinely supplanted by GenAI tools in academic work. Walther (2025) further revealed that mental deterioration happens in four progressive stages: the first is experimentation driven by curiosity to use a new tool; followed by technology adoption; the third stage is reliance, marked by growing dependence on GenAI tools; and lastly, the addiction stage, marked by loss of users' ability to function effectively without GenAI tools.

The overall effect of GenAI dependence is that it can usurp the power of human cognitive abilities and gradually weaken them, as supported by Darwin's theory of use and disuse (Elsayary & Ragab, 2025; Veigl, 2017). The risk of cognitive offloading among learners manifests in several ways: reduced critical thinking, and academic perseverance (Gerlich, 2025; Carmon, et al. 2027)); shift in epistemic practices, particularly in knowledge formation and verification (Yan et al., 2025), as learners simply ask an AI chatbot to generate and analyze text, thereby bypassing critical thinking and intellectual engagement thresholds that produce novelty in thought.

Given the understanding of how digital tools such as generative AI tools adoption triggers cognitive offloading, impair cognitive behavior, it is important to propose a framework that explains this phenomenon that leads to cognitive offloading and how to preserve human agency (Walther, 2025).

2.2. Theoretical Background

There is a paucity of Studies at the intersection of theory, GenAI, Cognitive offloading, and how to sustain cognitive autonomy, however, study by Klein and Klein (2025), suggested an emerging consensus across cognitive science, education, information systems (IS), and human-

computer interaction (HCI) research that cognitive offloading and decline in the age of AI are fundamentally an information system design and technology governance issue.

Moreover, previous studies suggested evidence of theories that support cognitive resilience, epistemic autonomy, and sustainable AI adoption among learners in educational institutions. These theories are extended cognitive theory (Oden, 2024), cognitive load theory (Kumar et al., 2026), self-determination theory (Zhou et al., 2024), constructivist learning theory (Cress & Kimmerle, 2023), self-regulated learning, and socio-technical theory (Agustin, 2026).

While these theories support the previous impact of information systems adoption on learners' cognitive abilities, they do not robustly project the current AI technological realities, where generative artificial intelligence systems have become intertwined with teaching and learning (Adesiji, 2024). Therefore, this study adopts a socio-materiality theory integrated with GenAI institutional governance to propose a framework that can give explanatory perspectives on the human-AI interaction in a learning environment and how to sustainably preserve human cognition in the adoption of generative AI in higher education.

Socio-materiality theory, propounded by Orlikowski (2007), explores the relationships between social (human) and material (technology) entities in information systems and organization research (Chedrawi & Haddad, 2022; Schultze et al., 2020). It relates to previous theories such as actor-network and sociotechnical theory, but has been improved by the idea of agential realism that presumes that the social and material agents are intertwined in organizational practices (Moura & Bispo, 2020). Socio-materiality claims that the mix of the social and the material entities assume no structural superiority; as such, learners and technology (generative AI) components have a dynamic relationship in a new learning environment.

Several studies reinforced the appropriateness of the socio-materiality theory lens for discussing GenAI-mediated learning, either directly or indirectly. These studies maintained that the pervasive impact of GenAI in education has created a blurred human-AI boundary (Yan et al., 2025); GenAI's impact in education has evolved beyond the simplistic human-vs.-machine dichotomy as expressed in some theoretical grounding (Gutoreva et al., 2026); GenAI tools are partners, as they already are a part of the fabric of our shared cognition (Dron, 2023); GenAI tools in learning re-echo distributed cognition (Calado, 2026).

More so, in a bid for new theoretical lens to understudy GenAI and cognition, a study by Popow (2026) expressed that GenAI has ruptured the ontological knowledge governance, transforming the foundations of epistemic authority and intellectual agency, as a consequence Yan et al. (2025)

expressed that scholars in educational practices must reframe human cognition as a hybrid process, collaboratively extended through real-time interaction with intelligent AI systems.

Socio-materiality is portrayed as a post-humanist orientation that is not anti-human, but shows how GenAI-mediated learning can stand parallel to human abilities and not replace them (Moura & Bispo, 2020). The principle of socio-materiality is a deviation from attributing hegemony to humans as the only agents in the learning environment capable of shaping learning (Moura and Bispo, 2020). In this study, the socio-materiality theoretical lens integrated with the GenAI institutional governance framework is used to both explain GenAI-mediated learning and to sustain cognitive autonomy.

2.3. Conceptual Model and Hypotheses Formulation

To properly adapt the socio-materiality theory as an explanatory framework for generative AI-mediated learning environments and to examine mechanisms for sustaining human cognition, this study integrates socio-material constructs with GenAI institutional governance to propose Perceived Cognitive Sustainability Socio-material Framework (PCSSF) comprises six core latent constructs: Socio-Material Entanglement (SE), Hybrid Minds (HM), Perceived Cognitive Offloading (PCO), Perceived Cognitive Decline (PCD), GenAI Institutional Governance (IG), and Cognitive Sustainability (CS).

2.3.1. *Socio-material Entanglement (SE) and Hybrid Minds (HM)*

Socio-materiality posits that humans and technology do not operate independently but shape one another through repeated engagement (Schultze et al., 2020; Sun, *et al.* 2026)). In GenAI-infused academic environments, learners do not interact with GenAI passively as query system, rather, their cognitive processes become deeply intertwined with GenAI-generated suggestions, summaries, answers, and real-time analytical feedback

This study contextualizes socio-materiality entanglement as the level to which students' learning activities combine social learning practices with the interactive affordances of GenAI tools (Leonardi, 2013). The interplay of learners' routine interaction with GenAI for problem-solving, blur the dynamic boundary between human cognition and technical agency, developing into an extended cognitive state contextualized as Hybrid Mind (HM). A hybrid mind represents an evolving cognitive scenario wherein human biological reasoning and GenAI computational capabilities jointly operate to achieve learning outcomes (Clark, 2025). Consequently, we hypothesize:

- H_1: *Socio-material entanglement (*SE*) is positively associated with the development of a Hybrid Mind (*HM*) among higher education learners*.

2.3.2. *Hybrid Minds (HM) and Perceived Cognitive Offloading (PCO)*

Hybrid mind in our context refers to an evolving thinking system in which human biological cognition and GenAI are fluidly combined to achieve an entangled learning outcomes (Clark, 2025; Yan et al., 2025). The fluid availability of an intelligent co-processor creates structural incentives for learners to delegate routine and complex mental operations to AI agents, a process conceptualized as Perceived Cognitive Offloading (PCO) (Piatnitckaia et al., 2025). In higher education, the perceived cognitive offloading manifests when learners delegate core analytical tasks such as literature synthesis, and idea generation to GenAI tools to accelerate completion times. While distributed cognition theory frames task-sharing as an efficient allocation of mental resources, unmonitored offloading within a hybrid cognitive structure increases reliance on automated outputs. Thus, we formulate:

- H_2: *The emergence of a Hybrid Mind (*HM*) is positively associated with learners' Perceived Cognitive Offloading (*PCO*).*

2.3.3. *Perceived Cognitive off-loading (PCO) & Perceived Cognitive Decline (PCD)*

In higher education, cognitive offloading yields short-term efficiency gains, however, excessive or unregulated delegation of core intellectual tasks risks triggering skill atrophy (Gutoreva et al., 2026; Piatnitckaia et al., 2025). According to Darwinian principles of use and disuse and neuro-scientific models of synaptic pruning, cognitive skills that are consistently outsourced to GenAI tools experience a gradual weakening of independent functionality (Walther (2025). In this study, Perceived Cognitive Decline **(**PCD**)** represents a learner's metacognitive awareness of reduced independent problem-solving ability, decreased critical thinking stamina, and diminished conceptual retention without technological assistance. When learners continuously rely on GenAI to bypass effortful intellectual struggle, they experience a decay in their independent academic reasoning and decision-making capacities (Agustin, 2026). Therefore, we hypothesize:

- H_3: *Perceived Cognitive Offloading (*PCO*) is positively associated with Perceived Cognitive Decline (*PCD*) among learners*

2.3.4. *Perceived cognitive Decline and GenAI Institutional governance (IG)*

While GenAI tools have positively influenced human performance, sustained over-reliance poses cognitive risks and diminished analytical autonomy (Anthuvan & Prabhuram, 2026)**.** In this study, we measure the relationship between perceived cognitive decline in the use of GenAI with GenAI institutional governance as follows:

- H_4: GenAI institutional governance (IG) is associated to *Perceived Cognitive decline (*PCD)

2.3.5. *GenAI Institutional Governance (IG) and Perceived Cognitive offloading (PCO)*

In cross-sectional research designs, individual-level perceived cognitive offloading cannot logically act as an antecedent that predicts macro-level institutional policy. Instead, in this study, institutional Governance **(**IG**)** functions as a structural was integrated buffer and mitigate cognitive risks associated with GenAI use within the higher educational environment (Lim & Bannert, 2026). The establishment of proactive GenAI governance in an educational institutions characterized by pedagogically designed assignments, critical evaluation mandates, and clear thresholds for technological reliance can constrain the unreflective use of GenAI tools that drives cognitive skill decay. Strong governance structures provide learners with institutional rules that regulate human–AI engagement, thereby directly dampening the perception of cognitive offloading. We therefore hypothesize:

- H_5: *GenAI Institutional Governance (*IG*) is strongly associated with Perceived Cognitive Offloading (*PCO*)*

2.3.6. *Perceived Cognitive offloading and Cognitive Sustainability (CS)*

Preserving intellectual autonomy in GenAI-infused higher education requires structural governance mechanisms that sustain cognitive engagement. Cognitive Sustainability **(**CS**)** in this study is construed as a learner's ability to retain, apply, and independently exercise critical reasoning, analytical evaluation, and problem-solving skills over time, even when supported by GenAI tools (Dacey et al., 2026). Against the chorused outright GenAI bans, effective use of GenAI use in offloading some mental tasks to AI is considered to foster self-regulated learning and cognitive sustainability, and augment learning practices. Accordingly, we hypothesize:

- *H_6: Cognitive offloading is strongly associated with cognitive sustainability (CS).*
- $H_{7:}$ *GenAI Institutional Governance (*IG*) is positively associated with Cognitive Sustainability (*CS*).*

The outcome of GenAI use in higher in the framing of socio-material theory and GenAI institutional governance emerges dynamically over time to form cognitive sustainability as shown in the study framework in Figure 1.

The conceptual framework in Figure 1 explains how perceived socio-material entanglement, human cognition, GenAI technologies, institutional structures are associated with sustainable cognitive outcome in educational practices.

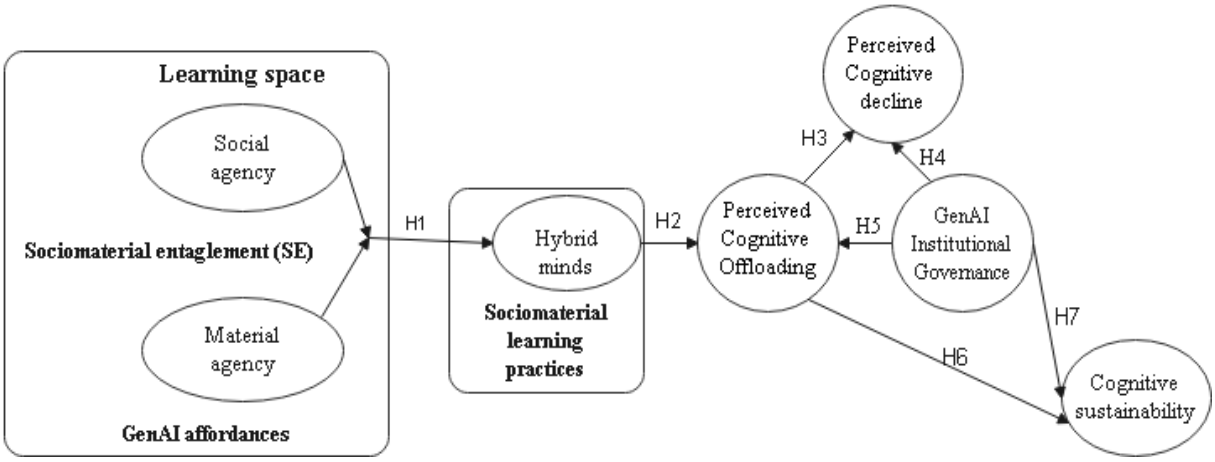


Figure 1. *Perceived Cognitive Sustainability Socio-material Framework (PCSSF) in a Generative AI Era*

3. Methodology

3.1. Research Design

This study adopted a quantitative and correlational research design using structural equation modeling (CB-SEM) to test and validate the research framework (Adawiya & Csíkos, 2026; Hair et al., 2025). In addition, an empirical literature search was conducted and combined with survey data collected from selected higher educational institutions within the northeast and north central of Nigeria. The research process followed this structured sequence of stages as described below.

3.1.1. *Reconciling the Ontological Barrier of Socio-materiality Theory in Quantitative Research Design*

This study diffused the Socio-materiality theory core ontological position of constitutive entanglement conflicts with the variable-separation logic that quantitative research design requires. Therefore, this study adopts socio-material theory grounded in critical realism that permits the analytical separation that quantitative methods require (Leonardi, 2013; Chedrawi & Haddad, 2022). This study used reflective survey indicators to measure the *enactment* and *perception* of separately, and reassembled them to reflect the experiences of human actors within socio-material ensembles (Kim & Yang, 2020).

3.1.2. *Operationalization of the Research Constructs*

This study employed survey-based indicators to measure self-reported experiential perceptions of participants and metacognitive awareness of cognitive offloading and skill reduction rather than direct neuro-biological measurement. The conceptual ordering of the research constructs in Figure 1: Socio-material entanglement (SE), hybrid minds/intelligence (HM), Perceived

Cognitive Offloading (PCO), Perceived Cognitive Decline (PCD), GenAI institutional governance (IG) and its association with Cognitive sustainability (CS).

3.1.3. *Design of the Measurement Instrument(s)*

The design of the research framework was done in conjunction with expert advice and research literature. In addition, a survey-based structured questionnaire was used to measure the constructs identified above. The instrument used a 7 Likert-type response format to measure the perceived responses from respondents, where higher values revealed greater agreement, while lower values indicate disagreement (1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = agree, and 7 = strongly agree). The detail of the questionnaire is attached (see Appendix).

3.1.4. *Determining the Appropriateness of the Research Instruments*

The study used pre-test study to evaluate the appropriateness of the research instrument with the help of four experts (three independent information system researchers with indepth knowledge of GenAI, and one educational technologist expert). These experts guided in developing the framework constructs and the associated questions.

3.2. Pre-test and Pilot Study

To determine the instrument reliability and questionnaire clarity, a pilot study was conducted with 25 respondents. The respondent's feedback helped to make changes to questionnaire.

3.3. Population size and Sampling

To have a representative sample from the study population, this study adopted Cochran formula to sample a population of 86 higher educational institutions within the northeast and north central regions of Nigeria.

The study assumes a confidence level of 95% (z = 1.96), a margin of error of 5%, and maximum variability (p = 0.5; q = 0.5) (Guilarte-Barinaga et al., 2026):

$$n = \frac{N \cdot p \cdot q \cdot z^2}{e^2 (N - 1) + z^2 \cdot p \cdot q}$$

Based on this formula, a sample of 71 higher educational institutions was obtained. Furthermore, at the individual level, participants were targeted across those 71 campuses, using proportional stratified random sampling based on student population enrollment quotas across University (48.1%), Polytechnic (34.8%), and College of Education (17.1%) strata. Therefore, 255 participants were targeted from the University, 234 participants from the polytechnic and

213 participants from the colleges of education to have a total number of 702 respondents. The number of participants in each institution of learning reflects the different institutions types and across students' types (undergraduate students, and postgraduate students/researchers). Out of the 702 participants targeted, 523 responses were returned from the institutions, however, 420 were considered valid after questionnaires with incomplete data were removed.

More importantly, In structural equation modelling, there are fragmented rules for determining sample sizes, but (Wolf et al., 2013) revealed that the sample size should be between 30 and 460 observation to establish meaningful patterns of association between constructs. Nicolaou and Masoner (2013) argue for maximum flexibility to accommodate a multi-study perspective, and making it adaptable to research environments where is difficult to obtain large dataset. Therefore, the intersection of the population sampling and structural equation modelling sample determination was coherent with a total observation of 420 samples. Table 1 presents the general characterization of the sample in terms of demography, percentage distribution and responses.

Table 1. *Respondents Category and Percentage Distribution*

Demography	**Distributions**	**Responses (N=420)**
Gender	Male	280(66.7%)
	Female	140(33.3%)
Age group	17 – 25 years	264(62.9%)
	26 – 35 years	77(18.3%)
	36 – 45 years	50(11.9%)
	46 years and above	29(6.9%)
Type of institutions	University	202(48.1%)
	Polytechnics	146(34.8%)
	Colleges of Education	72(17.1%)
Category of respondents	Students	321 (76.43%)
	Graduate/Researchers	99 (23.57%)

3.4. Data Analytical Tools

The study conducted tests of normality to ensure non-linearity of the items and the constructs to enable structural analysis of the dataset. More so, the descriptive statistics of the demographic section of the data were analyzed using SPSS, while the covariance-based structural equation modeling (CB-SEM) of IBM AMOS (Version 23) was used to analyze the measurement and the structural relationship of the research construct (Hair et al., 2025). In addition, to test mediation for hypotheses 5 and 6, the study used bootstrapping method with a pseudo-population of 5000 samples and 95% confidence interval. CB-SEM studio (Xavier, 2026) was used to represent the graphical display of the structural model.

3.5. Ethics Procedure

The study obtains formal written approval from the various educational institutions through the institutional review board (IRB) office, and each participant were assured of anonymity and allowed to participate through informed consent.

4. Results

4.1. Test of Normality and Common Method Bias Resolution

This study validated the assumptions of CB-SEM, including tests of normality and homoscedasticity before using IBM AMOS (v23) (Hair et al., 2025). The values for skewness (< 2.0) and kurtosis (< 7.0) fell within acceptable statistical thresholds.

To mitigate against Common Method Bias (CMB) in the cross-sectional surveys, two procedural and statistical controls were executed:

I. **Harman's Single-Factor Test:** An unrotated exploratory factor analysis (EFA) for all 24 indicator items revealed that a single factor accounted for only 20.5% of the total variance, well below the 50.0% threshold (Podsakoff et al., 2003).

II. **Unrelated Marker Variable Technique:** A theoretically unrelated four-item marker construct was included in the estimation model. The marker construct demonstrated non-significant correlations with all main study variables ($\beta = 0.02$ to 0.05, $p > 0.05$). These results confirm that common method variance seemed unlikely to confound the empirical findings.

4.2. Reporting of Research Constructs and Framework

Prior to estimating the measurement and the structural model of the research model, the confirmatory factor analysis (CFA) was evaluated. The research framework socio-materiality entanglement (SE), hybrid minds/intelligence (HM), Perceived cognitive offloading (PCO), Perceived cognitive decline (PCD), institutional governance (IG), and cognitive sustainability (CS), were assessed. These evaluated metrics included standardized factor loadings (FL), the assessment of internal consistency using Cronbach's alpha and composite reliability (CR), while convergent validity was evaluated through the average variance extracted (AVE) as shown in Table 2.

The results of Construct reliability and validity reported in Table 2 reveals that most of the factor loadings were greater than 0.7, but some were within the acceptable level of 0.5, which is acceptable (Hair, 2010). The Cronbach's alpha and the composite reliability were between 0.6

and 0.8, while the average variance extracted were above 0.4 except for SE and HM constructs. Largely supporting internal consistency of measurement items (Hair et al., 2025).

Table 2. *Items, Constructs Values, and Sources*

Constructs	Items	FL	α	CR	AVE	Source
Socio-material Entanglement (SE)	SE1	0.618	0.755	0.756	0.384	(Griffiths and Dickinson, *2024)*
	SE2	0.610				
	SE3	0.669				
	SE4	0.578				
	SE5	0.620				
Hybrid Minds (HM)	HM1	0.628	0.691	0.691	0.310	(Yan et al., 2025)
	HM2	0.541				
	HM3	0.536				
	HM4	0.522				
	HM5	0.552				
Perceived Cognitive Offloading (PCO)	PCO1	0.831	0.819	0.819	0.694	(Gerlich, 2025)
	PCO2	0.834				
Perceived Cognitive decline (PCD)	PCD1	0.827	0.815	0.815	0.688	(Westerbeek, 2026)
	PCD2	0.832				
GenAI Institutional governance (IG)	IG1	0.793	0.893	0.894	0.629	(Thaldar et al., 2025)
	IG2	0.788				
	IG3	0.759				
	IG4	0.860				
	IG5	0.755				
Cognitive Sustainability (CS)	CS1	0.780	0.885	0.886	0.609	(Dacey et al., 2026)
	CS2	0.786				
	CS3	0.785				
	CS4	0.817				
	CS5	0.731				

4.3. Measurement model

In this study, we evaluated the measurement model by examining the model fit, reliability, and validity of the model among the relational constructs (Shahzad et al., 2025). The model fit is determined by the values of the ratio of minimum discrepancy (CMIN/df), comparative fit index (CFI), adjusted goodness of fit index (AGFI), Tucker–Lewis index (TLI), normed fit index (NFI), root mean square error of approximation (RMSEA) and standardized root mean squared residual (SRMR). Table 3 revealed the results of the model fit in comparison with the approved threshold value for a good fit (Hair et al., 2025).

Table 3. *Model Fit*

Fit indices	Recommended criteria	Obtained value
CMIN/df	< 3	1.691
GFI	> 0.90	0.931
CFI	> 0.90	0.961
AGFI	>0.90	0.939
TLI	> 0.90	0.954
NFI	>0.90	0.952
RMSEA	< 0.080	0.041

The measurement model exhibited acceptable good fit: χ^2 = 400.767, df = 237, while the CMIN/df = 1.691; GFI = 0.931; AGFI = 0.939, NFI = 0.952; CFI = 0.961; TLI = 0.954; all within the 0.90 acceptable level, and RMSEA = 0.041. These model fits indices indicate that the hypothesized six-factor constructs were statistically significant and appropriate to measure the research framework. According to (Hair et al., 2025; Ximénez et al., 2022), the CMIN/df ratio of 1.691 (measurement) reflects an appropriate sample-to-model fit with low residual variance. Alongside RMSEA = 0.041, CFI = 0.961, and TLI = 0.954, these indices suggest good empirical fit without over-parameterization.

4.4. Reliability and Convergent Validity

Construct reliability was determined with summarized metrics such as the Cronbach's alpha (α), composite reliability (CR), and the average variance extracted (AVE) as shown in Table 4.

The Cronbach's alpha (α), and composite reliability were used to assess the internal consistency of the items in the constructs and to establish correlation among constructs (Hair et al., 2025), five (5) of the six constructs exceeded 0.70 and were significant, confirming the construct reliability, however, Cronbach alpha for construct HM was 0.691 which was close to 7. While the average variance extracted (AVE) score for measuring the variance between latent constructs, all were at acceptable threshold of 0.4 and above, except for SE = 0.384, and HM = 0.310. However, these values did not affect the overall model fits.

Table 4. *Reliability and Convergent Validity*

Constructs	No of items	Cronbach alpha (α)	Composite Reliability	Average Variance Extracted (AVE)
SE	5	0.755	0.756	0.384
HM	5	0.691	0.691	0.310
PCO	2	0.819	0.819	0.694
PCD	2	0.815	0.815	0.688
IG	5	0.893	0.894	0.629
CS	5	0.885	0.886	0.609

4.5. Discriminant Validity

More so, to measures the extent to which the constructs are empirically distinguishable from others in the model; discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio method (Shahzad et al., 2025). The Fornell-Larcker criterion assessed the correlation values of the cross-loading of the construct to ensure that the square root of the average variance extracted (AVE) was higher than the correlation coefficient of the vertical and horizontal rows and columns. As shown in Table 5, the values for each construct (ranges from 0.557 to 0.833) exceeded all corresponding inter-construct correlations threshold, and validating the Fornell-Larcher criterion.

Table 5. *Fornell–Larcker Criterion*

Constructs	AVE	SQRT(AVE)	SE	HM	PCO	PCD	IG	CS
SE	0.384	0.619	0.619					
HM	0.310	0.557	0.564	0.557				
PCO	0.694	0.833	0.220	0.225	0.833			
PCD	0.688	0.830	0.184	0.198	0.793	0.830		
IG	0.629	0.792	-0.046	0.010	0.457	0.412	0.792	
CS	0.609	0.780	-0.056	0.023	0.410	0.352	0.478	0.780

In addition, HTMT was established by assessing the correlation ratio of the cross-loading and the value was less than 0.85 (Hair et al., 2025), as shown in Table 6, all the 15 HTMT values were below 0.85, which established the HTMT criterion (Henseler et al., 2015).

The assessment of the results of both the Fornell-Larcher, and the HTMT ratio satisfy the discriminant analysis criteria. Therefore, the constructs validity, the convergent and discriminant results empirically support the research framework.

Table 6. *Heterotrait-Monotrait (HTMT) Ratio of Correlations*

Constructs	SE	HM	PCO	PCD	IG	CS
SE						
HM	0.764					
PCO	0.223	0.227				
PCD	0.181	0.196	0.793			
IG	0.089	0.063	0.458	0.418		
CS	0.085	0.067	0.411	0.352	0.479	

4.6. Structural Model Analysis and Hypothesis Testing

To assess the research structural relationship represented in the conceptual framework, the study re-evaluates the model fit for the full structural model as shown in Table 7. The structural

model fits exhibited acceptable to good fit: χ^2 = 407.485, df = 244, CMIN/df = 1.670, while GFI = 0.930; and AGFI = 0.937, NFI = 0.911; CFI = 0.961; TLI = 0.956; are all within the 0.90 acceptable levels, while RMSEA = 0.040. These model fits indices indicate that the overall hypothesized construct of the structural framework is good.

Table 7. *Model Fit for the Structural Model*

Fit indices	Recommended criteria	Obtained value
CMIN/df	< 3	1.670
GFI	> 0.95	0.930
CFI	> 0.90	0.961
AGFI	>0.90	0.937
TLI	> 0.90	0.956
NFI	>0.90	0.911
RMSEA	< 0.080	0.040

4.7. Model Structural Relationships

Furthermore, we estimate the structural relationships in the model to establish if they are significant enough to support the structural relationships. As shown in Table 8, the standardized path coefficients for the structural model relationship between the constructs in Table 8 were all positive and significant. In addition, the study reported the parameter estimates, standard error, T values, and p-values as shown in Table 8.

From Table 8**,** the result shows that seven hypothesized direct structural relationships in research framework. The relationship shows that six out of the seven are significant and satisfy the assumptions in the framework. This revealed that the proposed perceived cognitive socio-material sustainability framework integrated with GenAI institutional framework in this study which assumes that socio-material entanglement was associated with the creation of new cognition termed 'hybrid minds', and the hybrid minds is associated with perceived cognitive offloading and perceived cognitive decline.

Table 8. *Statistical Significance of the Paths Coefficient With P-Values*

Hypothesis	Paths	Estimate	Standard error (β)	T-values	P-Value	Decision
H1	SE → HM	0.863	0.103	8.402	***	Supported
H2	HHM → PCO	0.369	0.085	4.313	***	Supported
H3	PCO → PCD	0.774	0.066	11.733	***	Supported
H4	IG → PCD	0.040	0.033	1.198	0.231	Not Supported
H5	IG → PCO	0.292	0.035	8.245	***	Supported
H6	PCO →CS	0.370	0.090	4.087	***	Supported
H7	IG → CS	0.360	0.058	6.214	***	Supported

Note. *Significance of Correlations: p < 0.100, * p < 0.050, ** p < 0.010, *** p < 0.001*

The strongest association was seen between socio-material entanglement and hybrid minds (β = 0.863, p < 0.001) (H1), followed by the relationship between perceived cognitive offloading and perceived cognitive decline (β = 0.774, p < 0.001) (H3), and as well as between perceived cognitive offlaoding and cognitive sustainability (β = 0.370, p < 0.001) (H6). This was followed by the relationships between hybrid minds and perceived cognitive offloading (β = 0.369, p < 0.001) (H2) and between GenAI institutional governance and cognitive sustainability (H6). lastly, GenAI institutional governance and perceived cognitive offloading (β = 0.292, p < 0.001) (H5).

Hence, the GenAI institutional governance (IG) did not predict perceived cognitive decline (β = 0.040, p < 0.033) (H4). Within the scope of this study, Institutional governance could not predict mental degradation. This scenario can be properly investigated in the future by (longitudinal or experimental) research rather than a self-reported study. Figure 2 shows the enhanced IBM AMOS hypothesized structural relationships in the research conceptual framework.

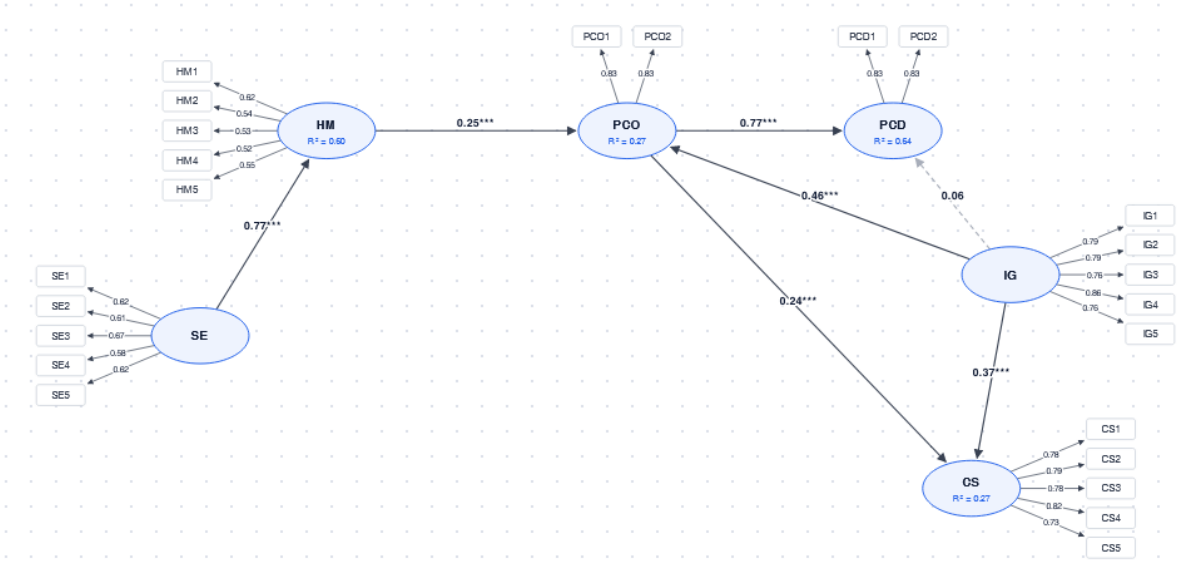


Figure 2. *Factor Loadings and Structural Paths Coefficients of the PCSSF Research Framework*

5. Discussions

This study presents covariance-based structural equation modeling (CB-SEM) analysis to test the structural relationships in the perceived Cognitive Sustainability Socio-material Framework (PCSSF). The CB-SEM analysis revealed that the proposed PCSSF could be associated with the preservation of learners' cognitive agency in Nigerian higher educational institutions with the integrated role of GenAI institutional governance in the model. The measurement and the structural models validated the hypothesized relationships in the framework. As shown in Figure 2, the latent variables measured by observed indicators depicted by circles: Socio-materiality entanglement (SE), hybrid minds (HM), perceived cognitive offloading (PCO),

perceived cognitive decline (PCD), GenAI institutional governance (IG), and cognitive sustainability (CS). The arrows between the constructs show structurally that the path coefficients and their association with other constructs in the proposed framework. The structural relationship in Table 8 revealed that 0.863 of socio-material entanglement was associated with hybrid minds (HM), while 0.369 of hybrid minds (HM) was associated with perceived cognitive offloading (PCO), 0.774 of perceived cognitive offloading (PCO) was associated with perceived cognitive decline (PCD). Additionally, as revealed in Table 8, GenAI institutional governance did not predict perceived cognitive decline (PCD) (H4). However, institutional governance shows associated with cognitive sustainability (H7). The structural model validation reveals that the constructs in the framework were associated with the concern of cognitive sustainability in the age of generative AI when the effects of the socio-material entanglement and the emergent of hybrid minds (HM) is integrated with GenAI institutional governance.

Despite the infrastructural and teacher-student ration issues in Nigeria higher education, the perception of students in the use of GenAI for study and learning suggest that the socio-material framework reinforces the creation of hybrid minds, and its associated perceived cognitive offloading and cognitive decline. However, GenAI institutional governance was perceived to show association with perceived cognitive offloading sustenance of cognition (Dacey et al., 2026). This result highlights that in the evolved socio-material entanglement in the use of GenAI in higher education, GenAI institutional governance could help to self-regulate learners in the use of GenAI (Lim & Bannert, 2026).

Our study aligns with previous studies that proposed the idea of mental co-creation and co-regulation of human and GenAI as Part of learners' cognition in the era of generative AI (Agustin, 2026; Gutoreva et al., 2026). However, our study differs by adapting socio-materiality integrated with GenAI institutional governance to unravel the new mental model in the use of GenAI, and how to remedy the cognitive effects of the hybrid minds.

5.1. Theoretical Implications

Theoretically, the contribution of this study lies in integrating theory and self-reported evidence into a single conceptual model and testing their joint relationships. The study integrates socio-material theory with GenAI institutional governance strategies but to explain the emerging hybrid minds and associated cognitive impact, and how the conceptual model could potentially preserve cognitive abilities of learners, advancing cognitive sustainability frameworks in the era of generative AI use in Nigerian higher educational institutions. Therefore, this study

suggests an opinion-based theoretical positioning based on the conceptual framework that Generative AI-induced cognitive offloading and decline is not solely a technological problem or a human social problem, but an emergent hybrid minds enabled by socio-material and GenAI institutional governance integrated phenomenon (Yan et al., 2025).

5.2. Practical Implications

This study outlines the following steps to preserve cognitive autonomy among students in Nigerian higher educational institutions:

- Educators should help students to understand the new hybrid minds created by GenAI-mediated learning and how to navigate it.
- Learners must be guided through thorough institutional guardrails such as AI literacy skill that emphasizes both technical skills, and impact on cognitive skills.
- Learners must know that GenAI use can augment human cognition, but does not supplant independent cognitive abilities.

6. Conclusion

The findings of this study reveal that the influence of socio-material entanglements has created hybrid minds in the use of generative AI in the higher educational process, leading to perceived cognitive offloading. However, the study framework validated in this study highlighted that the unintended consequences of cognitive offloading could be regulated by GenAI institutional governance strategies. This study concludes that a safe landing for learners' cognitive agency in an AI-infused learning is critically, creatively, and actively co-authoring it with the help of institutional governance rooted in adaptive learning methods that can work with GenAI technology.

The study framework constructs created clear epistemological boundary where we measured cognitive concerns by self-reported perceptions. Future study should explore the use of standardized experiment or longitudinal data to measure neuro-cognitive risks associated with the use of GenAI. Additionally, the reflective items capture perceived socio-material entanglement in our operationalization, this study further suggests that multi-method designs could further capture non-dualist agential realism to address the usual critique in survey-based research with the anti-dualist premises theory. Lastly, there should cautious generalization of the results to all regions of Nigeria, since the data collected was restricted to northeast and central regions of Nigeria.

Disclosure Statement

The authors declare that there is no conflict of interest regarding the publication of this article. No financial, personal, or professional relationships have influenced the research, analysis, or conclusions presented in this work.

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Appendix : Survey Questions

Category	Questions	Source(s)
Socio-material entanglement (SE)	1. Does the way you use GenAI for learning influenced by the people you study or work with? 2. Do the expectations of your lecturers influence how you use GenAI for academic work? 3. Does the way GenAI responds influence how you use it for academic tasks? 4. Does the features of GenAI shape the way you interact with it in learning? 5. Do your learning activities with GenAI combine both your practices and the capabilities of the technology?	(Griffiths and Dickinson, 2024)
Hybrid minds (HM)	1. Has GenAI become integrated into the way you think about difficult learning tasks? 2. Do you use generative AI to extend your own ability to solve problems? 3. Does GenAI perform some parts of a learning task while you perform other parts? 4. Does your thinking process incorporate ideas generated by AI? 5. Do you interact with generative AI as though it is a collaborative assistant?	(Yan et al., 2025)
Cognitive Offloading (CO)	1. Using GenAI for the analysis of academic sources is faster than my personal evaluation? 2. GenAI helps me to search for answers rather than other methods in problem solving?	(Gerlich, 2025)
Cognitive decline (CD)	1. Reliance on GenAI tools for academic work reduces my ability to think critically? 2. My ability to make academic decision decreases when I use GenAI tools extensively?	(Westerbeek, 2026)
GenAI Institutional governance (IG)	1. My institution provides clear guidelines on how students should use GenAI without reducing their own thinking and reasoning? 2. My institution encourages students to use GenAI as a support for learning rather than as a replacement for their own cognitive effort? 3. My institution has policies that encourage students to use and critically evaluate information generated by AI? 4. My learning activities encourage me to combine GenAI information with my own knowledge, reflection, and reasoning? 5. I am expected to disclose when I have used GenAI in completing academic work?	(Onunga, 2025)
GenAI Cognitive sustainability (CS)	1. Even when I use GenAI, I am able to maintain my ability to think independently about academic problems? 2. Using GenAI does not reduce my ability to critically evaluate information and reach my own conclusions? 3. I am able to retain and apply what I have learned even when GenAI assists me with academic tasks? 4. I can continue to solve academic problems on my own when GenAI is not available? 5. My use of GenAI helps me to learn, reason, and make decisions independently over time?	(Dacey et al., 2026)