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The Effect of Trust in Generative AI on Critical Thinking: The Mediating Role of AI Over-Reliance

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Abstract:

Trust is necessary for productive use of generative artificial intelligence (GenAI), yet excessive trust can shift cognitive work from the learner to the system. This study tests whether AI over-reliance mediates the relationship between trust in GenAI and critical-thinking disposition. We conduct a reproducible secondary mediation analysis using a public dataset of 2,614 Bangladeshi university students and construct-level statistics reported in its companion conference study. Trust in AI was strongly associated with cognitive dependence (r = .707). Using standardized ordinary least-squares mediation reconstructed from the published correlation matrix, the trust→dependence path was a = .707; the dependence→critical-thinking path controlling for trust was b = .150; the direct trust→critical-thinking path was c′ = .242; and the indirect effect was ab = .106 (delta-method SE = .018, z = 5.78, 95% CI [.070, .142]). The total trust–critical-thinking association was c = .348, so 30.5% of the observed association was carried through cognitive dependence. Importantly, the indirect path is positive in this self-report dataset, which does not support a simple "more dependence means less critical thinking" account. We interpret this pattern as a calibration paradox: high-trust students may simultaneously report stronger critical-thinking tendencies and stronger reliance, while behavioral studies can still show performance costs from uncritical acceptance. The paper contributes a dual-pathway framework that distinguishes trust, dependence, and verification quality, and derives design implications for GenAI-supported learning.

Keywords: *generative AI, trust, over-reliance, cognitive dependence, critical thinking, higher education, mediation analysis, human–AI collaboration..*

1. Introduction

1.1 Background and Context

Generative artificial intelligence has moved from a peripheral learning aid to an always-available cognitive partner capable of drafting, explaining, coding, summarizing, and recommending. In higher education, this shift changes not only how students obtain information but also how they allocate attention, effort, verification, and responsibility. Reviews of large language models in education emphasize both substantial instructional opportunities and risks related to inaccurate

outputs, assessment practices, and learner agency [23]–[25]. Systematic evidence in STEM education likewise shows that artificial intelligence can support personalization and feedback, while outcomes remain contingent on how learners interact with the technology [26].

A central variable in this interaction is trust. In human–automation research, trust helps users decide whether to rely on a system under uncertainty [3], and inappropriate calibration can produce either misuse through over-reliance or disuse through unwarranted rejection [4]–[6]. This distinction has become increasingly relevant for GenAI because fluent natural-language responses can be accepted without the verification normally applied to less persuasive tools. Classic automation-bias research documents omission and commission errors when people defer to automated advice [8], [9], while more recent work shows that cognitive forcing and appropriate-reliance designs can reduce blind acceptance of AI recommendations [12], [13].

Education adds a second concern: the cognitive work that is transferred to AI may be the very work students need to practice. Cognitive offloading can be adaptive when external tools free working resources for higher-level reasoning, but it can become maladaptive when the external system replaces analysis, monitoring, or memory processes that learners need to develop [10], [11]. Recent GenAI studies therefore distinguish strategic collaboration from dependency. Goh et al. developed a validated GenAI Dependency Scale and found that dependency was associated with lower task performance and lower critical thinking in one adult sample [18]. A systematic review by Zhai et al. similarly identifies risks to cognitive abilities when students become over-reliant on dialogue systems [19]. In parallel, Hou et al. show that critical thinking is related to reflective, cautious, and collaborative reliance behavior, whereas trust predicts more thoughtless use [17]. The recent study by Mai, Fang, and Cao offers a useful educational framing by connecting trust, over-reliance, learner autonomy, and STEM learning outcomes, and by emphasizing balanced rather than unconditional trust in AI tutors [16]. Its emphasis on trust calibration motivates the present study to isolate the statistical pathway from trust to critical thinking through over-reliance. The present work extends that line of inquiry from AI tutors to GenAI and from broad learning outcomes to critical-thinking disposition.

The empirical challenge is that trust, reliance, and critical thinking are often analyzed in separate models. The public Bangladesh dataset released by Arifen, Rahman, and Khandakar contains measures of GenAI usage, trust, critical thinking, academic decision-making, and cognitive dependence for 2,614 university students [1]. Its companion analysis reports construct means, reliabilities, correlations, and a regression predicting cognitive dependence [2], but does not decompose the trust–critical-thinking relationship into direct and indirect paths. This creates an opportunity for a non-fabricated secondary analysis based entirely on observed, published statistics.

This paper makes four contributions:

- It reconstructs a standardized mediation model from a verified public dataset and its published correlation matrix, using only the reported construct-level statistics.
- It quantifies how much of the trust–critical-thinking association is statistically carried through cognitive dependence, operationalized here as AI over-reliance.
- It identifies a calibration paradox: the mediated association is positive in this self-report sample, even though behavioral and clinical-education studies often associate dependency with weaker critical-thinking outcomes [18], [22].
- It translates the resulting dual-pathway model into concrete educational and interface design principles centered on verification, cognitive forcing, and calibrated rather than maximized trust.

II. THEORETICAL BACKGROUND AND HYPOTHESES

A. Trust as a Precursor to Reliance

Trust is commonly treated as an attitude that supports willingness to accept vulnerability to an automated system when outcomes cannot be fully inspected in advance. Lee and See's framework argues that appropriate reliance depends on the correspondence between trust and system capabilities [3]. Parasuraman and Riley distinguish use from misuse and disuse, locating over-reliance within automation misuse [4]. Empirical studies subsequently showed that trust predicts reliance decisions [5] and is shaped by dispositional, situational, and learned factors [6]. Research focused specifically on artificial intelligence reaches a similar conclusion: trust is neither inherently desirable nor undesirable; its value depends on whether it is calibrated to reliability, uncertainty, and task conditions [7].

GenAI intensifies the trust problem because linguistic fluency is not a direct signal of factual or inferential validity. A user can experience a response as competent before verifying whether it is correct. Explanations and confidence cues may improve calibration under some conditions [14], while interface explanations can also impose cognitive burden or encourage acceptance if users treat transparency as a blanket quality signal. Liao et al. therefore frame explainable-AI experiences around the questions users need to ask rather than around explanation volume alone [15]. In an educational context, a plausible first pathway is consequently straightforward: greater trust should be associated with greater cognitive dependence on GenAI outputs.

H1: Trust in GenAI is positively associated with AI over-reliance (cognitive dependence).

B. Over-Reliance, Cognitive Offloading, and Critical Thinking

Cognitive offloading is the use of external action or tools to alter the information-processing demands of a task [10]. Offloading is not intrinsically harmful. Calculators, notes, search engines, and tutoring systems can preserve scarce cognitive resources and support complex problem solving. The key educational distinction is between offloading that supports reasoning and offloading that substitutes for reasoning. Sparrow et al. demonstrated that access to external information can change what people remember and how they organize memory [11]. In GenAI settings, the substitution risk extends beyond information storage to argument generation, problem decomposition, and decision support. Recent evidence shows heterogeneous outcomes. Goh et al. report a small negative association between GenAI dependency and critical thinking in their U.S. adult sample [18]. Among medical students, Siva et al. found an inverse association between AI dependence and critical-thinking scores (Spearman rho = -.248) [22]. Tian and Zhang model AI dependency as one pathway in a double-edged relationship between perceived AI intelligence and critical thinking [20]. Si et al. distinguish strategic from habitual offloading and identify user profiles ranging from simple question-answer use to "critical co-thinking," illustrating that frequency of external support and retention of cognitive agency need not move in lockstep [21]. These findings caution against treating all reliance as equivalent. Hou et al. identify reflective, cautious, collaborative, and thoughtless reliance behaviors, with critical thinking linked to the more deliberative patterns [17]. This strategy-graded view implies that a self-report dependence score may correlate with intense GenAI engagement while not directly revealing whether the user verifies claims, generates alternatives, or retains final judgment. Therefore, the conditional association between dependence and critical thinking is treated as an empirical question rather than forced into a single directional assumption.

H2: AI over-reliance is significantly associated with critical thinking after controlling for trust in GenAI.

C. The Mediating Role of AI Over-Reliance

Mediation provides a useful decomposition of two conceptually different processes. The first is the direct trust pathway: trust may reduce interaction friction and encourage students to engage

with a capable tool, ask follow-up questions, or explore alternatives. The second is the reliance pathway: trust may increase the degree to which cognitive work is delegated to the system. If reliance is predominantly uncritical substitution, the indirect effect should be negative; if reliance co-occurs with active interrogation and higher overall engagement, the indirect association can be positive in self-report data. The direction therefore carries theoretical information about the kind of reliance captured by the measurement instrument.

H3: Trust in GenAI has a statistically significant indirect association with critical thinking through AI over-reliance.

III. METHODOLOGY

A. Data Provenance and Sample

The analysis uses the publicly documented Version 2 of "Dataset on Cognitive Dependence on Generative AI Tools among Bangladeshi University Students," released by Arifen, Rahman, and Khandakar on Mendeley Data under a CC BY 4.0 license [1]. The dataset contains 2,614 valid responses from students at public and private universities in Bangladesh. The repository description states that the survey covers GenAI usage, trust in AI systems, critical-thinking tendencies, AI-assisted academic decision-making, and cognitive dependence using five-point Likert items. The accompanying SPECTRA 2026 conference paper reports the construct-level statistics and correlation matrix used in this reanalysis [2].

The companion paper reports a sample consisting of 59.3% male and 40.6% female respondents; 44.7% attended public universities and 55.3% private universities; 60.7% were undergraduate and 39.3% postgraduate students [2]. Five constructs were measured with five items each. The present study operates at the level of published sufficient statistics and therefore does not require participant-level reconstruction.

Table 1DESCRIPTIVE STATISTICS REPORTED FOR THE PUBLIC DATASET

Construct	M	SD	α
GenAI Usage	3.80	.64	.479
Trust in AI	3.64	.75	.610
Critical Thinking	3.75	.68	.556
Academic Decision-Making	3.75	.68	.553
Cognitive Dependence	3.55	.87	.706

Note: N = 2,614. Values are reported in the companion analysis [2].

B. Construct Operationalization

Trust in AI is the focal predictor X and represents confidence in AI-generated outputs. Cognitive Dependence is the mediator M. In this paper, it is operationalized as AI over-reliance because the construct captures the extent to which students rely on GenAI for learning and problem-solving activities [2]. Critical Thinking is the outcome Y and represents self-reported tendency to independently analyze information. This operational definition is deliberately distinguished from behavioral verification accuracy or performance-based critical-thinking tests. The reliability coefficients in Table I range from .479 to .706. Cognitive Dependence has the strongest internal consistency (α = .706), followed by Trust (α = .610). The relatively modest reliability of the Critical Thinking scale (α = .556) makes the observed association conservative in some respects but also reinforces the need to interpret the construct as the specific self-report measure used in the source dataset rather than as a complete measurement of critical-thinking ability.

C. Summary-Statistic Mediation Estimation

For standardized variables, the simple mediation model can be recovered exactly from the three zero-order correlations among X, M, and Y. Let rXM denote the Trust–Dependence correlation, rXY the Trust–Critical Thinking correlation, and rMY the Dependence–Critical Thinking correlation. The standardized path from Trust to Dependence is a = rXM. The conditional coefficient for Dependence predicting Critical Thinking while controlling Trust is obtained from the two-predictor standardized regression:

$$b = (rMY - rXM\ rXY) / (1 - rXM^2). \quad (1)$$

The direct effect of Trust on Critical Thinking controlling Dependence is:

$$c' = (rXY - rXM\ rMY) / (1 - rXM^2). \quad (2)$$

The indirect effect is ab and the total effect is c = rXY. The identity c = c′ + ab provides an internal check on the reconstruction. Standard errors for b and c′ were computed from the standardized two-predictor OLS model. The uncertainty of ab was estimated with the first-order delta method (Sobel form). Fisher z intervals were used for the three source correlations. As a numerical robustness check, all three correlations were perturbed by ±.0005, corresponding to the maximum uncertainty implied by three-decimal reporting; the sign and substantive size of the indirect effect were unchanged.

The mediation model is an associational decomposition of cross-sectional statistics. It estimates whether the observed Trust–Critical Thinking relationship is statistically carried through Dependence; it does not require or assert temporal causality.

IV. RESULTS

A. Zero-Order Associations

The source correlation matrix shows that Trust is strongly associated with Cognitive Dependence (r = .707), while Trust has a moderate positive association with Critical Thinking (r = .348). Cognitive Dependence and Critical Thinking are also positively correlated (r = .321) [2]. With N = 2,614, the corresponding Fisher-z 95% confidence intervals are narrow: [.687, .726] for Trust–Dependence, [.314, .381] for Trust–Critical Thinking, and [.286, .355] for Dependence–Critical Thinking. H1 is therefore supported: students reporting greater trust also report substantially greater cognitive dependence.

Table 2KEY CORRELATIONS AND 95% CONFIDENCE INTERVALS

Association	r	95% CI
Trust–Dependence	.707	[.687, .726]
Trust–Critical Thinking	.348	[.314, .381]
Dependence–Critical Thinking	.321	[.286, .355]

B. Mediation Paths

Figure 1 and Table III summarize the reconstructed standardized mediation model. The a path from Trust to Cognitive Dependence is .707. After controlling for Trust, the b path from Cognitive Dependence to Critical Thinking remains positive and statistically significant (β = .150, SE = .026, t = 5.81, p < .001), supporting H2 as a nonzero conditional association. The direct path from Trust to Critical Thinking also remains significant (c′ = .242, SE = .026, t = 9.39, p < .001).

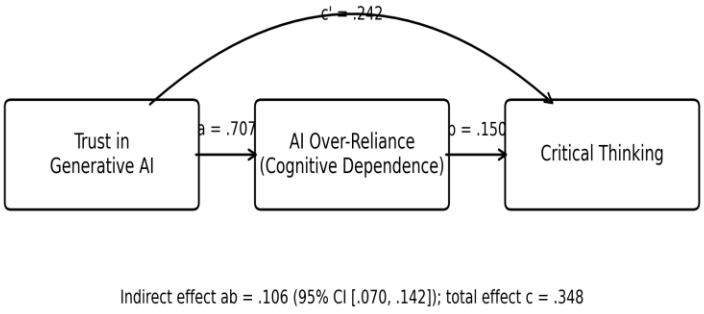


Figure 1Standardized mediation model reconstructed from the published correlation matri

Table 3STANDARDIZED MEDIATION ESTIMATES

Path	**Effect**	**SE**	**p**
a: Trust→Dependence	.707	.014	<.001
b: Dependence→CT | Trust	.150	.026	<.001
c′: Trust→CT | Dependence	.242	.026	<.001
ab: Indirect	.106	.018	<.001
c: Total	.348	—	<.001

The indirect effect is ab = .106. Its delta-method standard error is .018, producing z = 5.78, p < .001, with a 95% confidence interval of [.070, .142]. The total standardized Trust–Critical Thinking association is .348, and the direct-plus-indirect decomposition closes exactly within rounding: .242 + .106 = .348. The indirect component therefore represents 30.5% of the observed total association. H3 is supported.

Trust alone explains 12.1% of the variance in Critical Thinking (R^2 = .121). Adding Cognitive Dependence increases the explained variance to 13.2% (R^2 = .132; ΔR^2 = .011). Thus, Dependence adds a modest amount of unique prediction for Critical Thinking after the large shared variance between Trust and Dependence is considered. The partial correlation between Dependence and Critical Thinking controlling Trust is .113, whereas the partial correlation between Trust and Critical Thinking controlling Dependence is .181.

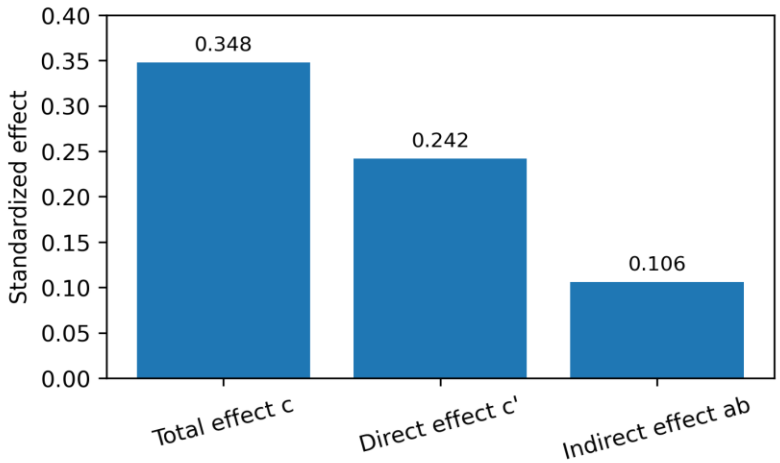


Figure 2Decomposition of the total Trust–Critical Thinking association into direct and indirect components.

Because the source matrix is reported to three decimals, a small sensitivity analysis varied each input correlation by ±.0005. Across all eight corner combinations, the indirect effect ranged from .105 to .107, b ranged from .148 to .152, and c′ ranged from .240 to .244. The substantive conclusion and the sign of every path are therefore not artifacts of decimal rounding.

D. Competing Cross-Sectional Decomposition

As a directionality check, a competing decomposition treated Critical Thinking as the mediator between Trust and Cognitive Dependence. In that model, the Trust→Critical Thinking path is a = .348; Critical Thinking predicts Dependence after Trust is controlled with b = .085; the direct Trust→Dependence coefficient is c′ = .677; and the indirect component is ab = .030 (delta-method 95% CI [.019, .040]). The indirect component represents 4.2% of the total Trust–Dependence association of .707. This competing decomposition does not identify temporal direction, but it shows that the large Trust–Dependence relationship remains essentially intact after Critical Thinking is controlled.

Table 4PRIMARY AND COMPETING ASSOCIATIONAL DECOMPOSITIONS

Decomposition	Direct	Indirect	Indirect/Total
Trust→Dependence →CT	.242	.106	30.5%
Trust→CT→Dependence	.677	.030	4.2%

Taken together with the primary model, the comparison is consistent with a dual-pathway account in which trust is tightly coupled to reliance, while the meaning of the reliance–critical-thinking link depends on what the measures capture. The result motivates direct measurement of verification behavior rather than treating self-reported dependence as a behavioral equivalent of uncritical acceptance.

V. DISCUSSION

A. Trust Is Primarily a Reliance Accelerator

The strongest empirical relationship in the model is the Trust→Dependence path (a = .707). This magnitude is consistent with decades of automation research in which trust functions as a key antecedent of reliance [3], [5], [6]. It is also compatible with the companion dataset analysis, where Trust was the strongest predictor of Cognitive Dependence among GenAI usage, trust, critical thinking, and academic decision-making [2]. The practical implication is that

interventions seeking simply to "increase trust" in educational GenAI may unintentionally increase delegation of cognitive work. Trust calibration is therefore a more precise target than trust maximization. This conclusion complements Mai et al.'s positive emphasis on balanced trust and learner autonomy in AI-tutor settings [16]. Their framework is valuable because it places trust and over-reliance in the same educational process rather than treating trust as an adoption variable only. The present mediation results add a quantitative decomposition showing that dependence carries a meaningful share of the trust–critical-thinking association.

B. The Calibration Paradox: Why Is the Indirect Path Positive?

The most informative result is not the existence of mediation but its direction. A simple cognitive-depletion account predicts Trust → more Dependence → less Critical Thinking. In the Bangladesh self-report data, however, Dependence remains positively associated with Critical Thinking after Trust is controlled ($b = .150$), yielding a positive indirect effect. This pattern should not be read as evidence that dependency causally improves critical thinking. Instead, it reveals that "dependence" and "critical thinking" can co-occur in self-reports and that reliance quantity is not equivalent to reliance quality. There are at least three theoretically coherent explanations. First, intensive GenAI users may simultaneously depend on the tool for many tasks and engage in more comparison, questioning, or reflection because they encounter more AI outputs. Second, students with stronger self-perceived analytical skills may feel more comfortable delegating subtasks precisely because they believe they can evaluate the result. Third, common self-report tendencies and the modest reliability of the source Critical Thinking scale can produce a pattern that differs from behavioral performance measures. None of these explanations requires assuming that uncritical dependence is beneficial. External evidence strengthens this interpretation. In Study 6 of Goh et al., GenAI dependency correlated negatively with critical thinking in a U.S. adult sample ($r = -.14$, $p = .038$) [18]. Siva et al. reported a stronger inverse association among 695 GenAI-using Indian medical students (Spearman $\rho = -.248$, $p < .001$) [22]. Hou et al. studied 808 undergraduates and separated reliance into reflective, cautious, collaborative, and thoughtless use; trust strongly predicted thoughtless use ($\beta = .47$, $p < .001$), whereas critical-thinking skills and dispositions were positively related to several deliberative forms of reliance [17]. In contrast, Si et al. identify heterogeneous offloading profiles, including a more critical co-thinking pattern [21]. Together, these studies suggest that the decisive variable is not whether students rely on AI, but how they rely on it.

C. From Reliance Amount to Reliance Quality

Human–AI research increasingly distinguishes reliance from appropriate reliance. Schemmer et al. conceptualize appropriate reliance in terms of accepting correct advice and rejecting incorrect advice [13]. In educational GenAI, an analogous quality criterion is whether learners maintain epistemic control: generating an initial representation of the problem, checking sources or calculations, testing alternative explanations, and retaining responsibility for the final answer. A student can therefore exhibit high interaction frequency and even high task-level dependence while still practicing verification; conversely, a student with infrequent AI use can accept the few outputs they receive without scrutiny.

This distinction explains why explanation alone is an incomplete remedy. Confidence and explanation can affect trust calibration [14], and explanation experiences should be designed around users' information needs [15]. Yet Buçinca et al. show that cognitive forcing can reduce over-reliance more directly than simple explanation displays, albeit with usability trade-offs [12]. For education, this points toward interfaces that require an active cognitive step before revealing or accepting a complete solution.

VI. DESIGN AND EDUCATIONAL IMPLICATIONS

A. Calibrate Trust Rather Than Maximize It

The Trust→Dependence coefficient indicates that changes in perceived reliability can have large downstream effects on reliance. Educational systems should therefore communicate uncertainty, scope, and known failure modes in task-relevant ways. Confidence cues should not be decorative; they should be tied to a concrete verification action such as checking an external source, rerunning a calculation, or comparing alternative solution paths. The goal is to make trust conditional on evidence and task context.

B. Introduce Productive Cognitive Friction

A second design principle is productive friction at moments where substitution would eliminate valuable reasoning practice. Before showing a full solution, a GenAI tutor can ask the learner to state a hypothesis, choose a method, or identify the next step. After providing an answer, the system can request an error check, counterexample, or confidence judgment. These mechanisms operationalize the cognitive-forcing logic demonstrated in AI-assisted decision making [12] without banning access to assistance. The friction should be concentrated on high-learning-value steps rather than applied uniformly.

C. Separate Verification Metrics from Usage Metrics

Institutions frequently track adoption, time-on-tool, or prompt counts, but these metrics cannot distinguish thoughtful collaboration from passive dependence. Evaluation should include verification behavior: whether students consult independent evidence, detect planted errors, revise AI outputs, or transfer concepts to no-AI tasks. This recommendation follows directly from the calibration paradox: self-reported dependence can coexist with self-reported critical thinking, so behavioral validation is necessary when the educational objective is cognitive autonomy.

D. Design for Transfer Beyond the AI-Supported Task

The most consequential outcome is not performance while assistance is present but performance when it is removed or when the model is wrong. Intelligent tutoring research has long shown that adaptive support can improve learning outcomes [28-30], but the GenAI setting requires explicit attention to transfer because the system can now perform a much larger portion of the reasoning chain. Assessments should therefore include delayed, no-AI, and adversarial-output conditions that reveal whether students learned the underlying method rather than only learned to operate the tool.

E. Evaluate Critical Thinking Across Three Conditions

A practical evaluation protocol can separate assisted performance from cognitive autonomy. First, an unaided baseline measures the learner's initial reasoning and confidence. Second, an AI-assisted phase records acceptance, rejection, revision, source checking, and confidence updating while the system presents a controlled mixture of correct and incorrect outputs. Third, a delayed no-AI transfer phase measures whether the learner can reproduce the reasoning on a structurally similar task. False acceptance of incorrect AI advice, successful correction of model errors, and transfer retention provide behaviorally grounded indicators that can be analyzed alongside trust and dependency scales. This three-condition design directly addresses the central ambiguity revealed by the present mediation results: reliance amount and verification quality are separable dimensions.

VII. VALIDITY, LIMITATIONS, AND FUTURE WORK

The study is a secondary analysis of cross-sectional construct-level statistics, so the path coefficients are associational and do not establish temporal causal effects. A longitudinal design would be needed to test whether trust at one time point increases later over-reliance and whether that, in turn, changes critical-thinking performance. Experimental manipulation of reliability,

confidence cues, or cognitive forcing could provide stronger causal identification. Measurement also warrants attention. The source scales are short five-item measures, and the reported Cronbach's alpha for Critical Thinking is .556 [2]. Future work should pair self-report dispositions with validated behavioral measures of verification accuracy, error detection, argument evaluation, and no-AI transfer. The GenAI Dependency Scale developed by Goh et al. provides a stronger multidimensional option for measuring dependency [18], while strategy-graded reliance measures such as those used by Hou et al. can separate cautious, reflective, collaborative, and thoughtless patterns [17]. Generalizability is also contextual. The source sample consists of Bangladeshi university students [1], [2], whereas published results from Singapore, the United States, China, and India show both convergent and divergent dependence–critical-thinking relationships [17], [18], [20]–[22]. A multi-country design using measurement-invariant instruments would determine whether the calibration paradox reflects culture, discipline, task type, or measurement method. Such work should also distinguish GenAI use for explanation and feedback from use for direct answer generation, because these interaction modes impose different cognitive demands.

Finally, future mediation models should incorporate trust calibration rather than trust level alone. Trust is appropriate when it tracks actual system reliability [3]. A learner who highly trusts a highly reliable output after verification is different from a learner who highly trusts an unreliable output without checking it. Models that include objective model correctness and user verification can therefore test a more mechanistic chain: system reliability → calibrated trust → strategy-graded reliance → critical-thinking performance.

VIII. CONCLUSION

Using verified statistics from a public dataset of 2,614 university students, this study decomposed the association between trust in GenAI and critical thinking through AI over-reliance. Trust was strongly related to cognitive dependence ($a = .707$). The indirect pathway through dependence was statistically significant ($ab = .106$, 95% CI [.070, .142]) and accounted for 30.5% of the total Trust–Critical Thinking association. At the same time, the indirect path was positive rather than negative in this self-report dataset. This result is important precisely because it resists a simplistic interpretation: greater reliance is not identical to weaker critical-thinking disposition, and self-reported critical thinking is not identical to demonstrated verification performance. The resulting dual-pathway framework places the educational focus on calibration and cognitive agency. Productive GenAI use should preserve the learner's obligation to formulate, verify, challenge, and transfer knowledge even when the system performs substantial cognitive work. For researchers, the next step is to combine validated dependency measures with behavioral critical-thinking outcomes and longitudinal or experimental designs. For educators and system designers, the immediate implication is to engineer conditions for appropriate reliance—neither reflexive rejection nor uncritical acceptance, but evidence-sensitive collaboration.

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