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AI Epistemic Disengagement and Consumer Dependence: An Augmentation-Substitution Framework

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ABSTRACT

Artificial intelligence has become consumers' primary decision-making resource, raising two questions: how do consumers justify accepting AI as a trusted source of reasoning, and when does this acceptance maintain rather than forfeit their capacity to think independently? Drawing on Bandura's moral disengagement theory, we introduce *AI epistemic disengagement*, a self-regulatory process through which consumers neutralize the discomfort of delegating reasoning to AI and justify reliance on it. In two studies with nearly 600 US consumers, we find two distinct patterns of AI dependence: augmentation and substitution. Augmentation maintains epistemic responsibility through conscientious evaluation, preserving consumer agency. Substitution abdicates epistemic responsibility through uncritical acceptance, making consumers vulnerable. These patterns differ in their antecedents and outcomes, consistent with Self-Determination Theory's distinction between autonomous and controlled motivation. Augmentation is associated with Need for Cognition and prompting skills, while the reverse holds for substitution. Augmentation, rather than substitution, is associated with intense AI use, habit formation, and broader application. Developing prompting skills, promoting epistemic responsibility, and designing interfaces that encourage critical thinking can help consumers, platforms, and policymakers preserve consumer welfare while supporting AI adoption.

1 | Introduction

Ninety-one percent of artificial intelligence (AI) users rely on their preferred AI tool for daily decision-making tasks (Carolan et al. 2025; OpenAI 2025). This "AI-first" mindset positions AI as an epistemic authority, a credible source of knowledge and reasoning (Zagzebski 2012), yet how consumers accept and justify this reliance on a system that thinks on their behalf remains unclear. While AI enhances efficiency and personalization, it risks algorithm over-dependence, skill decline (Kosmyna et al. 2025), and the erosion of consumer autonomy (Banker and Khetani 2019; Crisafulli et al. 2025; Du and Xie 2021; Ferraro et al. 2024). In particular, if consumers accept AI outputs without critical evaluation, they forfeit their capacity to think independently, which contradicts their own longstanding desire for autonomy and control in marketplace decisions (Fuchs et al. 2010). This tension reflects a central dilemma in consumers' use of AI: how to capture AI's benefits without surrendering the capacity for independent thought.

However, independent thought does not mean isolation from external sources of knowledge. Epistemic autonomy allows us to rely on others, whether they are humans or tools, as long as we provide our own reasons for trusting their judgment (Matheson and Lougheed 2021, p. 8). As King (2021, p. 55) notes, epistemic "autonomy requires thinking *for* ourselves, not *by* ourselves," a distinction central to the consumer dilemma between AI benefits and autonomy. The decisive factor is whether consumers retain epistemic responsibility, that is, actively evaluating AI outputs rather than passively accepting them (Corlett 2008), which depends on how consumers engage with AI (Rochi 2023). Two research questions arise: How do consumers justify accepting AI as an epistemic authority? When does this acceptance maintain rather than forfeit epistemic autonomy?

Bandura's theory of moral disengagement explains how individuals deactivate moral self-sanctions to justify unethical

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behaviors (Bandura 1991, 1999). We argue that a parallel self-regulatory process operates in the epistemic domain, which we term *AI epistemic disengagement*: consumers deploy cognitive justifications that neutralize the discomfort of delegating reasoning to AI, legitimating it as an acceptable epistemic authority. While disengagement enables acceptance of AI authority, it does not determine whether epistemic responsibility is maintained or abdicated. We suggest that AI epistemic disengagement (ED) gives rise to two distinct patterns of AI dependence: *augmentation* of cognitive capabilities through deliberate thoughtfulness (Dell'Acqua et al. 2025) or *substitution* of cognitive abilities through abdication of epistemic responsibility. Both patterns require ED: even reflective AI users must first neutralize the discomfort of delegating reasoning before integrating AI into their cognitive process. They differ, however, in their underlying motivations, explained through Self-Determination Theory (SDT) (Deci et al. 2017).

Across two studies with approximately 600 US consumers, we test our research questions. Study 1 develops and validates a measure of ED. Study 2 validates the AI augmentation and substitution framework and examines behavioral consequences. This study contributes to the consumer-AI interaction literature (Mariani et al. 2022) in four ways. First, it introduces ED as a self-regulatory mechanism that explains consumer acceptance of AI as an epistemic authority. Second, it distinguishes between augmentation and substitution as two different motivational pathways linking disengagement to AI use. Third, it identifies Need for Cognition (NFC) and prompt engineering as factors that separate augmentation and substitution patterns. Fourth, augmentation, rather than substitution, is associated with more intensive AI use, further confirmed through robustness checks, including AI habit and the breadth of AI use.

2 | Theoretical Background and Hypotheses Development

2.1 | Reliance on Technology

Technologies from writing systems to calculators have extended memory, reasoning, and coordination (Clark and Chalmers 1998; Norman 1993), with humans remaining the ultimate arbiters of reasoned thought. AI simulates advanced reasoning, raising the prospect that people will become less thoughtful, replacing reflection with passivity (Alvarado 2023; Coeckelbergh 2025). Yet consumers internalize norms of independent reasoning that shape their self-concept as competent decision-makers. Despite these norms, they nonetheless accept AI as an epistemic authority. We propose ED as a mechanism explaining this unexplored tension.

2.2 | ED: The Self-Regulatory Mechanism Enabling Authority Acceptance

Within Social Cognitive Theory, self-regulation is governed by internalized standards: individuals monitor their behavior, evaluate it against those standards, and apply self-reactive sanctions when they fall short (Bandura 1991). This regulatory process can be suspended; disengagement mechanisms allow individuals to selectively deactivate their standards and neutralize self-censure, a pattern observed across diverse behavioral domains (Bandura 1996; de la Fuente et al. 2022). In the epistemic domain, consumers internalize standards of independent reasoning and critical thinking, central to how they see themselves as intellectually competent (Code 2020; Zagzebski 2012). *AI epistemic disengagement* is the mechanism through which these standards are selectively deactivated: consumers deploy cognitive justifications that neutralize the discomfort of accepting AI's epistemic authority.

Encounters with AI can present a technology-induced threat to human identity, experienced as discomfort, particularly in domains individuals consider their own (Mende et al. 2019). Specifically, delegating reasoning to AI can elicit cognitive dissonance, as it conflicts with self-standards of competent and autonomous decision-making; the resulting epistemic discomfort is analogous to the guilt that moral transgressions generate (Seran et al. 2025; Stone and Cooper 2001). Consider a consumer who consults AI to save time on a product decision, feels uneasy about surrendering judgment, yet proceeds, telling themselves it is simply more efficient. This tension between the commitment to independent reasoning and the temptation to rely on AI reflects a self-standard conflict that disengagement mechanisms resolve.

Disengagement mechanisms function as a specific form of dissonance reduction (Gosling et al. 2006): just as moral disengagement deploys justifications that neutralize guilt, AI ED deploys justifications that neutralize this discomfort and legitimize AI as a credible epistemic agent. We adapt Bandura's (1999) eight mechanisms to the epistemic domain (Table 2). Consumers may engage in *epistemic justification*, framing AI dependence as a sensible way to handle complex thinking; use *euphemistic labeling* to describe delegated reasoning to AI as optimization of cognitive resources; rely on *advantageous comparison* positioning AI as more accurate than their own thinking; invoke *displacement* and *diffusion of responsibility*, attributing epistemic authority to the system or to emerging norms ("everyone uses AI for hard thinking"); exhibit *distortion of consequences* by minimizing AI's downsides; express the *humanization* of AI by emphasizing its human-like qualities (in juxtaposition to the dehumanization of a person in moral disengagement), whereby AI is perceived as possessing intelligence or intentionality; and engage in *attribution of blame*, externalizing responsibility. Through these mechanisms, AI ED functions as epistemic authority legitimation: consumers neutralize self-sanctions by redefining AI reliance as epistemically acceptable.

2.3 | The Augmentation–Substitution Framework of AI Dependence

King (2021) describes epistemic autonomy as the balance between two intellectual vices: servility, which involves outsourcing one's entire intellectual life to others, and isolation, the unrealistic ideal of forming beliefs entirely on one's own. Our framework presents AI augmentation dependence (AIAugD) as a virtuous pattern of embracing AI while maintaining epistemic responsibility through conscientious engagement (Zagzebski 2012). AI thus serves as a scaffold for reflection, exploration, and creativity, extending the consumer's reasoning capacity while they retain evaluative oversight and ownership of their

beliefs. These are necessary conditions for epistemic autonomy (King 2021; Matheson and Lougheed 2021).

By contrast, AI epistemic substitution represents the vice of servility, with autonomy forfeited due to the abdication of epistemic responsibility. Consumers who initially use AI to save time may gradually cease cross-checking its outputs and stop forming independent judgment altogether (Kim et al. 2026), surrendering their epistemic autonomy through cognitive offloading (Risko and Gilbert 2016). In marketplace terms, augmentation involves making informed choices with AI while maintaining consumer autonomy, a core value in marketplace interactions (Dahl and Moreau 2007). In contrast, substitution may make consumers vulnerable by encouraging uncritical acceptance of AI recommendations in purchases, health, and financial decisions (Longoni et al. 2019). Table 1 summarizes these conceptual distinctions.

SDT (Deci et al. 2017) suggests that these two dependence patterns differ fundamentally in their motivational character. Augmentation reflects autonomous motivation, where AI engagement is self-endorsed, aligns with the user's values, and enhances competence while maintaining volitional control. In contrast, substitution reflects controlled motivation where consumers delegate cognitive tasks to AI on demand for convenience or effort avoidance rather than intrinsic motivation. Because ED enables acceptance of AI as an epistemic authority without determining how epistemic responsibility is subsequently managed, we hypothesize that:

H1. *ED is positively associated with AI epistemic substitution.*

H2. *ED is positively associated with AI epistemic augmentation.*

2.4 | Cognitive and Relational Antecedents of ED

NFC reflects individuals' intrinsic motivation to engage in and enjoy effortful thought (Cacioppo and Petty 1982) and is integral to individuals' sense of identity (Njus and Johnson 2008). From a self-regulatory perspective, individuals with high-NFC seek to maintain cognitive vigilance and resist delegating reasoning to others. In contrast, individuals with low NFC seek cognitive ease, which makes them more likely to disengage and accept external epistemic authority. Therefore, for high-NFC consumers, delegating reasoning to AI threatens the coherence of their self-concept. It follows that NFC is expected to be negatively associated with ED. Beyond this association, NFC is also expected to be associated with the dependence patterns themselves. Low-NFC users are more likely to substitute their own decision-making and offload the cognitive task (Risko and Gilbert 2016). High-NFC users are more likely to use AI to augment their reasoning and maintain control and evaluation. This aligns with research that shows high-NFC consumers interact more deeply with decision aids and maintain evaluative control (Haugtvedt et al. 1992). We therefore hypothesize that:

H3a. *NFC is negatively associated with ED.*

H3b. *NFC is negatively associated with AI epistemic substitution.*

H3c. *NFC is positively associated with AI epistemic augmentation.*

We posit that AI trust and anthropomorphism show the opposite association pattern from NFC. When consumers trust in AI's abilities, they are more likely to rely on it (Lee and See 2004), perceiving the system as dependable and credible (Glikson and Woolley 2020; Peng and Yeh 2025). This aligns with the view that trust encourages consumer acceptance of algorithmic recommendations (Lourenço et al. 2020). Anthropomorphism refers to the practice of attributing human-like traits to technology (Waytz et al. 2014). It strengthens AI's authority by framing it as a credible cognitive partner with human-like qualities such as intelligence and intentionality, creating perceptions of human warmth and social presence (Moriuchi 2021). Perceived humanness enhances consumer engagement with AI while elevating expectations about their empathic and cognitive capabilities (Pizzi et al. 2025), further facilitating the acceptance of AI as an epistemic authority. We therefore hypothesize that:

H4. *Trust in AI is positively associated with ED.*

H5. *Anthropomorphism is positively associated with ED.*

AI prompt engineering capability refers to users' ability to create, refine, and evaluate prompts to elicit meaningful responses from AI (Theoharakis et al. 2025). Effective prompting requires iteratively forming hypotheses, interpreting feedback, and critically evaluating AI outputs. From a self-regulated learning perspective (Zimmerman 2002), these tasks require conscientious monitoring and evaluation, maintaining epistemic responsibility even when partially delegating reasoning to AI. Therefore, as users integrate skillful AI interaction into their own cognition to improve insight, creativity, and reasoning, higher prompt capability should enhance augmentation. The absence of this skill is characteristic of substitution, since prompt engineering is a reflective process empowering users as autonomous epistemic agents and makes them less likely to view AI as a cognitive substitute. We therefore hypothesize:

TABLE 1 | Conceptual distinctions between AI epistemic authority, responsibility, and autonomy.

Concept	Definition	AI Dependence pattern	
		Augmentation	Substitution
AI epistemic authority	Recognizing AI as a credible, competent source of knowledge and reasoning	✓ Yes	✓ Yes
Epistemic responsibility	Practicing evaluative oversight, verification, and justification of knowledge claims	✓ Maintained	✗ Abdicated
Epistemic autonomy	Maintaining evaluative authority and self-governed control over one's beliefs independently of the knowledge source	✓ Preserved	✗ Forfeited

H6a. *AI prompt engineering capability is positively associated with AI epistemic augmentation.*

H6b. *AI prompt engineering capability is negatively associated with AI epistemic substitution.*

2.5 | AI Dependence Consequences

According to Self-Determination Theory (SDT; Deci et al. 2017; Ryan and Deci 2000), augmentation aligns with the need for autonomy, as consumers maintain volitional control and self-direction. Users perceive AI as a tool that expands their abilities and encourages competence and cognitive mastery. Augmentation maintains epistemic responsibility through active prompting, evaluation, and integration. When consumers repeatedly interact with AI in ways that meet their psychological needs, these interactions may reinforce one another, contributing to greater overall AI use (Deci et al. 2017; Radel et al. 2017). Substitution, on the other hand, reflects controlled motivation. In this case, individuals allow AI to think for them, abdicating epistemic responsibility and forfeiting autonomy. SDT suggests that controlled behaviors lacking self-endorsement are associated with less ongoing engagement than autonomous behaviors. While substitution inevitably results in some use, it does not provide the intrinsic rewards and need satisfaction for intensive engagement. Therefore, the association of augmentation with AI use intensity is likely to be greater than that of substitution:

H7. *AI epistemic augmentation has a greater positive association than AI epistemic substitution with AI use intensity.*

While our hypothesis focuses on the differential association between dependence patterns, we also consider the direct associations between AI ED and our behavioral outcomes (Figure 1). This specification adheres to the practices for mediation modeling, which include direct effects (Hayes 2018), and enables us to empirically investigate whether our dependence patterns fully mediate the association between disengagement and outcomes. Beyond use intensity, we also examine AI habit and the breadth of AI applications as robustness checks, as detailed in Study 2. Together, these behavioral outcomes capture distinct dimensions of AI integration, frequency, automaticity, and range, reflecting whether dependence patterns translate into sustained and expanding AI engagement.

3 | Study 1: Scale Development and Hypotheses Testing

3.1 | Overview and Objectives

Study 1 has three objectives. First, to establish AI ED as a psychometrically reliable construct that is distinct from related concepts. Second, to validate the measurement of substitution dependence. Finally, to test hypotheses about relationships among NFC, ED, and substitution. Following standard scale development procedures (Churchill 1979), we generated items based on the disengagement mechanisms, evaluated psychometric properties using exploratory and confirmatory factor analyses, and tested initial hypotheses using structural equation modeling.

3.2 | Method

3.2.1 | *Sample and Procedure*

We recruited 300 US consumers through Pollfish, a crowdsourcing platform with a broad reach (Esch et al. 2025). Respondents were screened to ensure they used AI (e.g., ChatGPT, Claude, Gemini, or similar generative AI systems) for everyday tasks at least once a month. This requirement ensured participants had enough experience to offer informed assessments. The platform also filtered out respondents who did not pass the majority of four predefined attention checks based on infrequency items (Maniaci and Rogge 2014). Participants completed measures in a randomized order to minimize order effects. The study protocol received approval from one of the co-authors' universities and was pre-registered. All participants provided informed consent.

3.2.2 | *Measures*

For AI ED, we adapted Bandura (1991) eight moral disengagement mechanisms to the epistemic domain. Consistent with prior research, we treat moral disengagement as a unidimensional reflective construct, adapting items from previously published scales (Moore 2016; Theoharakis et al. 2025). We generated 16 initial items, with two per mechanism. An expert panel consisting of two marketing researchers and two AI ethics scholars reviewed our items, and we made revisions based on their feedback (Table 2).

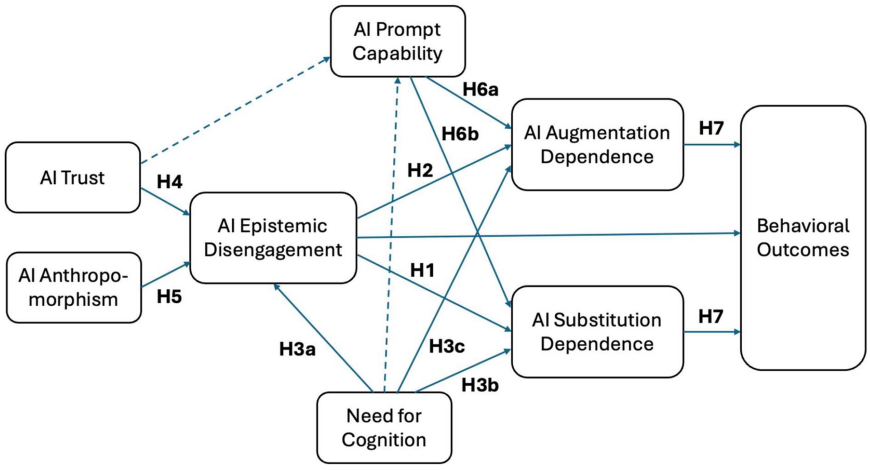

FIGURE 1 | Conceptual model. Dashed lines indicate paths included in the revised model. Hypothesis labels are displayed on each path.

TABLE 2 | Epistemic disengagement scale items.

Mechanism	Scale items
Epistemic Justification	1. It is okay to let AI handle complex thinking rather than struggling myself.* 2. There is little reason to think through the details when AI can do it better.
Euphemistic Labeling	3. Using AI for critical thinking is being efficient with my mental resources.* 4. Letting AI analyze problems is using technology smartly.
Advantageous Comparison	5. It is better to trust AI analysis than risk making a decision on my own information. 6. It is better to use AI evaluation rather than risk relying on my own critical assessment.*
Displacement of Responsibility	7. Since AI can reason through things better, I do not need to do it myself.* 8. I don't need to verify AI's analysis since that's what the system is designed to handle for me.
Diffusion of Responsibility	9. People shouldn't be blamed for relying on AI analysis when others around them are doing the same. 10. Everyone relies on AI for the hard thinking, so I do not need to do it all on my own.*
Distortion of Consequences	11. The downsides to using AI for analysis are minimal.* 12. Letting AI handle the analysis will not harm anyone.
Attribution of Blame	13. The complexity of modern problems leaves me no choice but to use AI.* 14. I need AI because there is too much information for me to verify everything myself.
Anthropomorphic Justification	15. AI thinks through problems like a caring, wise friend would.* 16. AI analyzes situations like a thoughtful human advisor.

Note: *Retained items.

The items measuring AI Substitution Dependence (AISubD) were adapted from the AI Misconduct scale (Theoharakis et al. 2025), which examined the misuse of AI in academic settings. We changed the focus from misconduct to cognitive dependence ("... without evaluating/verifying/formulating my own thoughts/forming my own understanding" and "I rarely question..."). This shift captures the extent to which individuals abdicate epistemic responsibility by accepting AI outputs without critical evaluation, thereby weakening their own epistemic agency and independence (Code 2020). The adaptation process was based on theoretical perspectives on epistemic dependence, which describes how individuals rely on others for knowledge (Hardwig 1985), and epistemic ownership, which emphasizes the responsibility to deliberate before accepting beliefs as one's own (Corlett 2008). The AISubD scale comprises five items (see Supporting Information S1: Appendix Table A1 for full wording). NFC was measured using the Enjoyment of Cognitive Stimulation subscale from the original NFC inventory (Cacioppo et al. 1984; Cacioppo and Petty 1982). This subscale reflects the individuals' intrinsic motivation to engage in and enjoy challenging cognitive tasks. Responses for all items used 7-point Likert scales (1 = *Strongly Disagree*, 7 = *Strongly Agree*). We also included age and gender as demographic controls.

3.3 | Results

In summary, Study 1 confirmed that ED is positively associated with substitution and that NFC serves as a protective factor against both disengagement and substitution.

From the 300 responses collected, 48% were male, and the mean age was 39.9 (SD = 10.8). After our screening, participant usage frequency indicated substantial AI engagement: 10% used AI monthly (a few times a month), 18% weekly (once a week), 33% several times a week (2-3 times per week), 19% daily (once a day), and 20% multiple times daily. We first refined the

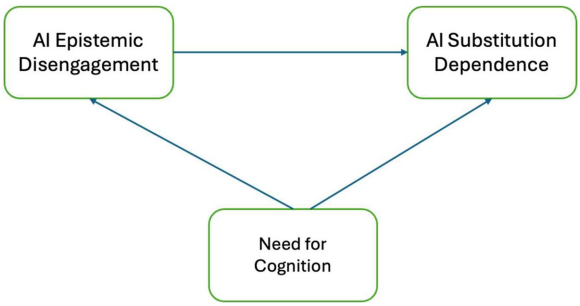

FIGURE 2 | Study 1 conceptual model.

16-item AI ED pool using Item Response Theory (IRT) analysis for developing a more parsimonious scale (STATA 18.5). We retained eight items, one per mechanism, selecting those with the best combination of discrimination ($\alpha \geq 2.0$) and threshold coverage across the latent trait continuum (Embretson and Reise 2013). This helped ensure theoretical breadth and psychometric precision (Table 2). Exploratory factor analysis (EFA) revealed a single factor, which accounted for 64.7% of the variance. Confirmatory factor analysis (CFA) supported a unidimensional factor structure, with excellent fit indices and all loadings exceeding 0.70, confirming that the items represent a single latent construct (χ^2 (18) = 29.02; CFI = 0.99; TLI = 0.99; RMSEA = 0.045; SRMR = 0.022) with excellent composite reliability ($\rho = 0.91$). Further, all items of the AISubD scale were retained, as each demonstrated strong discrimination ($\alpha \geq 2.0$) and adequate threshold coverage in IRT analysis.

To establish discriminant validity and test the conceptual model for Study 1 (Figure 2), a CFA to examine ED's relationship against conceptually adjacent constructs, such as NFC and AI Epistemic Substitution, provided a very good fit (χ^2 (129) = 212.40; CFI = 0.98; TLI = 0.97; RMSEA = 0.047; SRMR = 0.045). The composite reliability was also excellent for the remaining constructs in this study: NFC ($\rho = 0.85$) and AI substitution dependence ($\rho = 0.91$).

TABLE 3 | Construct statistics and correlations (Study 1).

Variables	Mean	SD	CR	AVE	(1)	(2)	(3)
(1) ED	4.07	1.34	0.91	0.571	0.756		
(2) NFC	4.50	1.30	0.85	0.530	−0.495	0.728	
(3) AISubD	3.14	1.44	0.91	0.664	0.634	−0.614	0.815

Table 3 displays means, standard deviations, and correlations, including our discriminant validity assessment, which shows that the square root of the average variance extracted (AVE) for each construct exceeds the correlations between constructs (Fornell and Larcker 1981). Altogether, these analyses provide strong support for the reliability, validity, and theoretical distinctiveness of the AI ED construct.

We tested our proposed model (Figure 2) to explore the hypotheses present in Study 1 (H1, H3a, and H3b). Our SEM model showed a very good fit (χ^2 (161) = 243.87; CFI = 0.98; TLI = 0.97; RMSEA = 0.041; SRMR = 0.047). H1 was strongly supported: AI ED is positively associated with epistemic substitution dependence ($\beta = 0.422$, $t = 7.66$, $p < 0.001$, $\eta^2 = 0.22$). This finding indicates that consumers who use disengagement justifications exhibit significantly greater uncritical AI dependence. H3a and H3b were also strongly supported: NFC is negatively associated with ED ($\beta = -0.576$, $t = 12.49$, $p < 0.001$, $\eta^2 = 0.25$) and also had a significant negative direct association with substitution ($\beta = -0.473$, $t = 6.76$, $p < 0.001$, $\eta^2 = 0.21$). These results indicate that consumers who enjoy cognitive effort are less likely to justify transferring epistemic authority to AI and less likely to substitute their own epistemic responsibility. This holds even after accounting for the mediating role of disengagement, in which NFC is directly and indirectly ($\beta = -0.243$, $t = 5.52$, $p < 0.001$) negatively associated with substitution, indicating *partial* mediation. From our controls, neither age nor gender had a significant association with AI Epistemic Substitution.

3.4 | Discussion

Study 1 established AI ED as a psychometrically reliable construct distinct from the NFC and substitution dependence. It produced two key findings. First, the strong positive relationship between ED and substitution supports the proposition that disengagement is associated with uncritical AI Substitution Dependence (H1). In this way, it validates our adaptation of Bandura (1991) moral disengagement framework to epistemic contexts. Second, NFC is negatively associated with both justifications for accepting AI epistemic authority (AI ED) and AI substitution dependence.

4 | Study 2: Validating the Augmentation-Substitution Framework

4.1 | Overview and Objectives

Study 2 addresses three limitations of Study 1 while providing a comprehensive test of the framework (Figure 1). First, we develop and validate an augmentation measure. This allows us to test the framework's two-dimensional structure and discriminant validity between augmentation and substitution. Second, we extend beyond NFC to explore additional antecedents, testing how cognitive, skill-based, and relational factors differentially predict each of the dependence patterns. Third, we investigate whether augmentation and substitution diverge in their association with AI use intensity, habit formation, and the breadth of AI use.

4.2 | Method

4.2.1 | *Sample and Procedure*

A sample of 300 US consumers was recruited through Prolific using the same screening criteria as Study 1. After excluding 10 participants (4.7%) who did not pass the same attention checks as Study 1, 290 participants remained (49% female; $M = 42.01$, SD = 11.09). The usage distribution was similar to Study 1: 10% used AI monthly (a few times a month), 15.5% weekly (once a week), 35.2% several times a week (2–3 times per week), 13.4% daily (once a day), and 25.9% multiple times daily. The study protocol received approval from one of the co-authors' universities and was pre-registered. All participants provided informed consent.

4.2.2 | *Measures*

We kept all constructs from Study 1: the 8-item AI ED AI Epistemic Substitution Dependence, and NFC, and included the additional relevant measures for Study 2 (Supporting Information S1: Table A1). We created AIAugD items as an adaptation of the *AI Substitution Dependence* scale. Substitution items focus on reliance on cognitive offloading and epistemic abdication. In contrast, we reworded Augmentation dependence items to reflect active, reflective AI engagement where users rely on AI to expand their reasoning. The adaptation shifted the emphasis from *delegation* to *collaboration*. We based our development on extended cognition (Clark and Chalmers 1998) and a human-centered AI perspective (Shneiderman 2022), which frames AI as a cognitive partner that augments rather than substitutes thought. The items measure how individuals use AI to generate ideas, broaden their thinking, challenge assumptions, and improve problem-solving.

AI Trust was assessed using four items from the AI S-TIAS scale (McGrath et al. 2025), based on the trust scale by Jian et al. (2000). AI Anthropomorphism was measured using five items adapted from Patrizi et al. (2024), based on the scale developed by Waytz et al. (2010). Prompt Engineering was adapted from Theoharakis et al. (2025), operationalized as specific prompting behaviors: providing examples, referencing source documents, decomposing complex tasks, and iteratively refining AI responses. Use intensity was measured using 3 items assessing the frequency and depth of AI consultation (how frequently,

what proportion of time, light or heavy use). AI habit was measured using 3 items capturing the automaticity and routinization ("Using AI … has become automatic/natural/a habit for me") of AI use (adapted from Theoharakis et al. 2025). Application breadth was operationalized as the number of distinct AI use categories reported by participants (e.g., writing, research, decision-making, creative tasks), providing a behavioral count measure that does not rely on Likert-scale self-reports. Use intensity and habit are self-reported measures; breadth, while also self-reported, is a behavioral count measure less susceptible to common method variance (CMV). As in Study 1, we controlled for age and gender. Full item wording for all measures is provided in Supporting Information S1: Appendix Table A1.

4.3 | Results

Study 2 validated the augmentation–substitution framework across all hypothesized relationships. ED was positively associated with both dependence patterns at comparable magnitudes, confirming its role as a general enabling mechanism rather than a pathway-specific one. NFC and prompt engineering capability differentiated the two patterns in opposing directions, and augmentation, not substitution, was consistently associated with greater use intensity, habit formation, and application breadth, aligning with SDT's predictions regarding autonomous versus controlled motivation.

4.3.1 | *Measurement Model*

CFA using maximum likelihood estimation (STATA 18.5) assessed the full measurement model (Figure 1). The model fit was very good (χ^2 (810) = 1143.18; CFI = 0.96; TLI = 0.96; RMSEA = 0.038; SRMR = 0.054). All factor loadings were significant, indicating that the items strongly represent their intended constructs. Table 4 presents descriptive statistics and correlations. Augmentation ($M = 4.95$, SD = 1.22) significantly exceeded substitution ($M = 2.68$, SD = 1.25) with $t(289) = -23.64$, $p < 0.001$. This suggests that accepting authority with responsibility is more common among regular AI users than without it. Augmentation and substitution were uncorrelated ($r = 0.08$, ns), with the square root of AVE for each construct being greater than its intercorrelation (Fornell-Larcker criterion), confirming discriminant validity. These findings support the framework's core premise: augmentation and substitution are distinct patterns of accepting AI authority.

CMV was assessed using Harman's single-factor test (the highest single-factor variance explained was 10.4%), and construct correlations were well below 0.90 (Pavlou et al. 2007), confirming it was not a concern. We controlled for social desirability using a brief version of Marlowe-Crowne's scale.

4.3.2 | *Conceptual Model Testing*

We estimated a structural model to test all hypothesized relationships of our conceptual model (Figure 1). The model fit is overall acceptable (χ^2 (791) = 1255.64; CFI = 0.94; TLI = 0.93; RMSEA = 0.045; SRMR = 0.082). However, since the SRMR is slightly above the recommended 0.08 level, we examined the modification indices for any missing paths that may not have been included in our model. The modification indices suggested adding two paths: NFC and trust as antecedents of prompt engineering, which aligns with our conceptualization. Both NFC and trust in AI are positively associated with the development of Prompt Engineering capability. Indeed, the added paths improve model fit, and we use this as our base model (χ^2 (789) = 1226.39; CFI = 0.94; TLI = 0.94; RMSEA = 0.044; SRMR = 0.071).

Our findings support H1 and H2. AI ED is positively associated with AI epistemic substitution ($\beta = 0.497$, $t = 9.39$, $p < 0.001$, $\eta^2 = 0.19$), and AI epistemic augmentation ($\beta = 0.465$, $t = 9.31$, $p < 0.001$, $\eta^2 = 0.19$) at very similar levels. NFC is negatively associated with ED (H3a: $\beta = -0.188$, $t = 3.66$, $p < 0.001$, $\eta^2 = 0.05$) and epistemic substitution (H3b: $\beta = -0.305$, $t = 5.34$, $p < 0.001$, $\eta^2 = 0.09$). However, it is positively associated with epistemic augmentation ($\beta = 0.191$, $t = 3.55$, $p < 0.001$, $\eta^2 = 0.04$) as predicted by H3c. We also confirm the positive associations of two hypothesized antecedents of AI ED trust ($\beta = 0.535$, $t = 11.16$, $p < 0.001$, $\eta^2 = 0.28$) and anthropomorphism ($\beta = 0.277$, $t = 5.27$, $p < 0.001$, $\eta^2 = 0.09$). AI prompt engineering capability is positively associated with AI epistemic augmentation (H6a: $\beta = 0.462$, $t = 8.69$, $p < 0.001$, $\eta^2 = 0.20$) but negatively with epistemic substitution (H6b: $\beta = -0.158$, $t = 2.68$, $p < 0.01$, $\eta^2 = 0.03$). Additionally, NFC ($\beta = 0.237$, $t = 3.80$, $p < 0.001$, $\eta^2 = 0.04$) and trust ($\beta = 0.301$, $t = 4.95$, $p < 0.001$, $\eta^2 = 0.09$) are positively associated with prompt engineering.

TABLE 4 | Construct statistics and correlations (Study 2).

Variables	M	SD	CR	AVE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ED	3.76	1.19	0.87	0.521	0.722								
(2) AIAugD	4.95	1.22	0.90	0.669	0.458	0.818							
(3) AISubD	2.68	1.25	0.90	0.657	0.475	0.121	0.811						
(4) NFC	4.83	1.41	0.91	0.685	−0.274	0.095	−0.425	0.828					
(5) Trust	4.74	1.22	0.95	0.812	0.599	0.426	0.394	−0.142	0.901				
(6) Antro	2.72	1.42	0.91	0.661	0.419	0.220	0.360	−0.115	0.296	0.813			
(7) Prompt	5.24	1.04	0.78	0.507	0.211	0.516	−0.064	0.152	0.243	0.077	0.712		
(8) Habit	4.20	1.61	0.94	0.841	0.528	0.516	0.352	−0.128	0.444	0.334	0.312	0.917	
(9) Use	4.59	1.04	0.83	0.638	0.445	0.481	0.127	0.084	0.338	0.212	0.396	0.677	0.799
(10) Breadth	3.43	1.59	—		0.306	0.391	0.110	0.107	0.186	0.151	0.363	0.426	0.575

H7 predicted that augmentation would have a stronger positive association with use intensity than substitution. Results indicated that augmentation is significantly associated with use intensity ($\beta = 0.373$, $p < 0.001$), but substitution shows no significant association ($\beta = 0.120$, $p = 0.10$). After estimating the structural model, we constrained the augmentation and substitution paths to be equal. This constraint significantly worsened model fit (χ^2 (1) = 30.34, $p < 0.01$), supporting H7. To assess the robustness of this finding, we examined two alternative outcomes: AI habit formation and the breadth of AI applications. While use intensity and habit are correlated ($r = 0.677$), they represent different aspects (frequency vs. automaticity). Breadth is less susceptible to CMV since it does not rely on Likert-scale self-reports. Wald tests across models confirmed significant differences in the association of AIAugD and AISubD with all outcomes: habit formation (χ^2 (1) = 6.35, $p < 0.05$) and application breadth (χ^2 (1) = 17.84, $p < 0.001$). These findings indicate that responsibility-maintaining AI dependence (augmentation) is associated with sustained, deep, and broad AI integration, while responsibility-abdicating dependence (substitution) is not.

AI ED has a significant direct association with Use Intensity ($\beta = 0.392$, $p < 0.001$) and AI Habit ($\beta = 0.318$, $p < 0.001$), but not application breadth ($\beta = 0.153$, $p = 0.07$). Justifying AI authority is thus associated with greater frequency and automaticity. In contrast, breadth expansion is associated exclusively with augmented engagement (Table 5).

4.4 | Study 2 Discussion

Study 2 validates the augmentation-substitution framework. Augmentation and substitution are empirically distinct (based on our CFA) and uncorrelated constructs, and ED, operating as epistemic authority legitimation, is associated with both at comparable magnitudes ($\eta^2 = 0.19$), consistent with its role in removing friction rather than predetermining outcomes. NFC and prompt engineering differentiate the two patterns in opposing directions, with prompt engineering showing the sharpest differentiation ($\eta^2 = 0.20$ for augmentation vs. $\eta^2 = 0.03$ for substitution). Trust shows the strongest association in the model ($\eta^2 = 0.28$ with disengagement). This suggests that trust operates as a permissive antecedent: high-trust consumers with strong NFC may channel disengagement into augmentation, whereas those with low NFC are more likely to channel disengagement into substitution. Augmentation is consistently associated with all behavioral outcomes across main and robustness tests; substitution is not. Disengagement is directly associated with intensity and habit, but not with breadth.

5 | General Discussion

This paper examines a key consumer dilemma: how can AI-assisted consumer decision-making allow consumers to maintain epistemic autonomy? Epistemic autonomy does not require epistemic independence, the fiction of forming all beliefs entirely on one's own (Fricker 2006). It permits reliance on trustworthy tools and others, provided consumers retain evaluative oversight (Clark and Chalmers 1998; Hardwig 1985; Kawall 2024). Yet the prospect of deferring to non-human intelligence evokes unease and reluctance to accept AI as a legitimate epistemic authority (Dietvorst et al. 2015; Longoni et al. 2019).

Following Bandura (1999), we introduce and empirically test AI ED as the mechanism associated with acceptance of AI as an epistemic authority. ED is positively associated with trust (Klingbeil et al. 2024) and anthropomorphism (Moriuchi 2021), and negatively associated with the NFC. Further, augmentation and substitution as the two patterns of AI dependence are distinct and not polar opposites (Raisch and Krakowski 2021). ED is associated with the acceptance of AI authority without determining augmentation or substitution (Horowitz and Kahn 2024). Our findings suggest that risks to epistemic autonomy arise not from AI use per se, but from patterns of engagement in which evaluative responsibility is abdicated.

In particular, autonomous augmentation is associated with higher NFC, effective prompting, and more intensive, habitual, and broad AI use. These findings align with consumer behavior research indicating that consumption experiences supporting autonomy lead to increased engagement and satisfaction (Dahl and Moreau 2007). In contrast, controlled motivation does not sustain long-term involvement (Ryan and Deci 2000). Substitution, characterized by lower NFC and limited prompting skills, is not significantly associated with the intensity or breadth of use. These findings are consistent with research showing that individuals higher in NFC engage more analytically with AI recommendations and are less prone to heuristic reliance (Buçinca et al. 2021), suggesting that cognitive motivation shapes how AI is engaged.

The robustness tests show that augmentation has a stronger association with habit than substitution. Augmentative AI engagement involves skilful practice to pursue deliberate gains (Thomas et al. 2024), consistent with the habit formation process of reward-motivated reinforcement (Wood and Rünger 2016). In contrast, substitution users' limited prompting skills (Zamfirescu-Pereira et al. 2023) and lower NFC weaken the reinforcement necessary for habit development (Ryan and Deci 2020).

TABLE 5 | Direct associations of epistemic disengagement and dependence patterns with behavioral outcomes.

	Use intensity	AI habit	Breadth
ED	0.392 (0.084)**	0.318 (0.077)**	0.153 (0.085)
AIAugD	0.373 (0.067)**	0.370 (0.060)**	0.355(0.066)**
AISubD	0.120 (0.073)	0.156 (0.065)*	−0.025 (0.073)

Note: Standardized path coefficients with standard errors in parentheses.
Abbreviations: AIAugD = AI augmentation dependence; AISubD = AI substitution dependence; ED = AI epistemic disengagement.
*$p < 0.05$; **$p < 0.01$.

5.1 | Theoretical Contributions

Our findings contribute to marketing theory by explaining how consumers manage the autonomy-dependence dilemma within an AI-mediated context.

First, we apply insights from moral disengagement theory to epistemic contexts. We demonstrate that Bandura's self-regulatory framework (Bandura 1999) is applicable more broadly to the study of technology acceptance. Our empirical evidence supports this moral-to-epistemic parallel: disengagement mechanisms are associated with reduced resistance to accepting AI authority. Accepting AI authority through ED is neither inherently virtuous nor problematic; it is a rational choice when individuals can maintain autonomy (Hardwig 1985; Matheson and Lougheed 2021; Zagzebski 2012).

Second, we find augmentation and substitution as empirically distinct patterns of AI epistemic dependence. These patterns are shaped by individual differences and skills that can be acquired through learning. This framework operationalizes King (2021) philosophical position: substitution parallels intellectual servility, while augmentation accepts authority while maintaining evaluative control. For marketing scholars, this framework expands consumer empowerment (Fuchs et al. 2010) and autonomy (Dahl and Moreau 2007) in AI settings.

Third, we identify cognitive and competence antecedents determining which pattern emerges. NFC and prompting capability exert opposing associations with augmentation and substitution, showing that high cognitive engagement and prompting skill support autonomy-preserving acceptance, while low cognitive motivation and limited skill encourage epistemic abdication. These findings emphasize the role of motivation and capability in epistemic responsibility in human-AI interaction. This has direct implications for AI platform design and consumer education.

Fourth, in line with SDT (Deci et al. 2017), we show that augmentation is associated with higher levels of use, habit formation, and broader application. In contrast, substitution limits engagement and is not associated with high levels of repetitive use. This suggests that designs promoting autonomy are both ethically desirable and practically achievable for AI platforms.

5.2 | Practical Implications

Our findings suggest actionable directions for practice.

AI interface designers could structure interactions to encourage consumers to remain reflective and in control. Design principles can include supporting the deliberation of choice criteria before recommendations are made, presenting AI outputs as starting points rather than final answers, adding reflection checkpoints, and clearly communicating the limitations. Such design choices align commercial incentives (sustained engagement) with consumer welfare (preserved autonomy).

Brand managers face a challenge as epistemic authority shifts to third-party AI applications beyond their control. Substitution may erode direct customer relationships, whereas augmentation can preserve consumer engagement with brand information. This managerial dilemma reflects the broader tension identified by Pizzi et al. (2025), who note that generative AI redefines authenticity, agency, and transparency in consumer–brand interactions. Strategic priorities include creating content that encourages reflection, educating consumers on effective prompting, and positioning brands around informed choice.

Policymakers might focus on capability development rather than restricting access or issuing warnings. Such traditional regulatory approaches focus on the pitfalls of substitution and overlook the benefits of augmentation. They could support AI literacy programs that enhance prompting competence and establish standards for the design of augmentative platform interfaces. Similarly, educational institutions could progress beyond policies limiting the use of AI in students' assignments and proactively cultivate epistemic responsibility and productive prompting.

5.3 | Limitations and Future Directions

Several limitations warrant discussion. First, our cross-sectional design limits our ability to make causal inferences. The model may also operate recursively: repeated AI use can strengthen trust, which, in turn, can reinforce disengagement and ultimately lead to more self-reinforcing habitual use. Longitudinal studies should investigate whether augmentation and substitution patterns are stable across user types or if they depend on specific contexts. For example, in high-stakes domains such as health or financial decisions, substitution may carry greater epistemic risk than in routine consumer tasks. Second, experiments can determine whether interventions aimed at improving prompting skills and awareness of epistemic responsibility can shift users from substitution to augmentation patterns. Third, both crowdsourcing platforms have been shown to produce reliable, attentive responses, and we employed infrequency-based attention checks, which are more robust than standard bogus-item checks (Esch et al. 2025). Nonetheless, our samples are limited to U.S. consumers who use generative AI at least monthly, and results may differ in professional contexts, specialized fields, or groups with different cultural norms regarding technology use. Fourth, use intensity and habit rely on self-report; future research could incorporate behavioral trace data to complement these measures. Application breadth, as a count measure, is less susceptible to this concern. Fifth, although we control for social desirability, augmentation and substitution items differ in their valence, which may still inflate augmentation and suppress substitution scores through self-presentation motives. Future research should complement self-report measures with behavioral indicators to empirically validate autonomy claims and to clarify whether the near-zero augmentation–substitution correlation may partly reflect independent self-concept affirmations rather than behaviorally distinct modes of engagement. Sixth, our framework does not consider how broader technology orientations, such as technology fatigue or digital detox motivations, may interact with augmentation and substitution patterns. Such an examination could yield a more holistic view of how consumers manage technological dependence. Finally, while our study establishes the augmentation-substitution framework and its antecedents, it does not examine marketing outcomes. Future research should investigate how augmentation versus substitution patterns affect decision quality, satisfaction, and brand relationships, as well as consumer welfare outcomes, including decision satisfaction and regret.

6 | Conclusion

As AI becomes increasingly integrated into daily life, preserving epistemic autonomy is crucial. Our research shows that autonomy is not automatically preserved or lost with AI use. It is maintained by practicing epistemic responsibility. Whether AI expands human cognition or substitutes for it, risking cognitive decline, depends on our willingness to remain its critical evaluators. Cultivating prompt engineering competence and designing augmentation-oriented interfaces encouraging critical thinking can help consumers, marketers, and policymakers harness AI's potential while protecting consumer agency.

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Ethics Statement

There is no conflict of interest. Ethical approval was obtained from one author's university, and our studies were pre-registered. Participants were fully informed of their rights, and data confidentiality was assured.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
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AI epistemic disengagement and consumer dependence: an augmentationsubstitution framework

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