

The double-edged sword of AI dependency: how cognitive offloading and skill atrophy foster digital complacency

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Abstract

Purpose – The current study examines the cognitive implications of an addictive use of generative artificial intelligence (AI) tools, and it theorizes that AI dependency triggers a cascade of mediation involving cognitive offloading and skill atrophy that results in digital complacency. Using the tenet of Distributed Atrophy Model, the study develops and tests an integrated model.

Design/methodology/approach – The data were collected through an online cross-sectional survey from 303 professionals (mostly aged 25–45) across technology-intensive and other AI-adopting knowledge work sectors (Information Technology, Higher Education, Finance and Banking, and Consulting) who use generative AI on a regular basis in their work-related activities. The proposed model was tested by using structural equation modeling (SEM-AMOS) that entailed confirmatory factor analysis of measurement validity and bootstrapped path analysis (5,000 resamples) to assess direct and mediated effects.

Findings – The results revealed that AI dependency positively predicted cognitive offloading, which had a strong impact on skill atrophy and skill atrophy was the strongest predictor of digital complacency. The direct impact of AI dependency on digital complacency was significant, which was serially mediated by cognitive offloading and skill atrophy. The model accounted for 36% of the variance in digital complacency.

Originality/value – Since the emergence of AI, most research has mainly focused on the positive implications of technology. But there are new indications that AI has the capacity to produce negative outcomes as well. Furthermore, the available literature is still fragmented, and various paths have not been thoroughly studied. To fill this gap, the current study discusses the negative consequences of AI dependency by developing and testing an integrated model to offer a more detailed insight into its cognitive and behavioral impacts.

Keywords AI dependency, Cognitive offloading, Skill atrophy, Digital complacency, Human–AI interaction, Structural equation modeling

Paper type Research article

Introduction

The ever-growing evolution of artificial intelligence (AI) is redefining the way people learn, work and make decisions (Cox *et al.*, 2019), but this transformation is especially visible among digitally immersed professionals and emerging leaders, including but not limited to Generation Z, who work in environments where algorithmic tools and intelligent assistants are readily available (Savin *et al.*, 2024). ChatGPT, Gemini and AI copilots are becoming more popular AI platforms that help students and professionals increase their productivity, performance and efficiency (Joshi, 2025), personalization (Rane *et al.*, 2024) and quality of decisions than ever before to enter the daily routine of studying and working (Bilal *et al.*, 2025). Leaders and organizations, both in organizational and educational contexts, promote the use of these tools as means to gain efficiency and competitive advantage (Sposato, 2024). The growing presence of AI is currently fascinating students and working professionals;



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however, it is creating a far-reaching impact on the cognitive abilities of individuals (Kang, 2023), particularly on younger, digitally immersed professionals.

Today's professionals, particularly younger and digitally immersed cohorts, have now been placed in the world of high-paced environments where the demands to deliver results quickly, stay connected and conduct data-driven performance only increase the pressure to make AI a first and not secondary tool (Chan and Lee, 2023). With AI taking over jobs that require the retrieval of information, writing, analytics and structuring of a problem, a small behavioral change occurs, i.e. more challenging cognition tasks are being left to machines. Although this form of delegation makes work much faster and more precise, it can also undermine the motivation to work with complex problems on a new level (Parker and Grote, 2022), critical thinking (Darwin *et al.*, 2024) and self-directed study. However, it is not the point for leaders whether AI should be practiced in the workplace or any other settings or not; the point is that overreliance on AI can lead to cognitive offloading and skill atrophy, which further leads to digital complacency and hinders the future labor force and leadership pipeline (Van Quaquebeke *et al.*, 2025).

Specifically, within the context of organization leaders, the impact of AI dependency on digital complacency is sequential: the more leaders depend on AI to make meaning of complex environments, create coherent stories and coordinate group action, which are important indicators of cognitive offloading. Due to the habitual nature of cognitive offloading, leaders might start not paying much attention to AI-generated summaries, scenario analyses and recommendations. Such a change may lead to superficial sensemaking and less pattern recognition and a loss of anomaly detection or the formation of new strategic reactions. These trends have a direct effect on the quality of decisions since excessive dependence reduces the deliberative aspect, moral judgment and tacit skills that define a good leader rather than an administrator. At the organizational level, widespread skill atrophy among early-career professionals and emerging leaders undermines capability development systems, threatening the long-term resilience of learning cultures, talent pipelines and adaptive capacity.

Although there is a sufficient body of literature available where managers came to the view that AI should be adopted, there is still little empirical evidence that can be used to understand how long-term habitual dependence on AI influences the way of thinking, learning and developing abilities (Davidson *et al.*, 2026). The current study extends existing research on digital complacency and cognitive offloading in four ways. First, existing research has mostly studied these phenomena in relative isolation (i.e. complacency as mindlessness in automated systems or offloading as a temporary cognitive strategy); the Distributed Atrophy Model posits them as causally interdependent steps in a vicious developmental cycle that evolves over time when one uses the service regularly (Jadhav, 2025). Second, it shifts away to a more predictive, mediational, theory of how and why early efficiency benefits may result in functional deterioration in memory, analytical depth, initiative and strategic judgment, especially when AI tools are viewed as very believable and frictionless (Klein and Klein, 2025). Third, where much of the automation literature remains centered in high-stakes sectors like aviation or process control, the current study extends these dynamics to the context of daily leadership and organizational learning, with strategic implications regarding the development of the workforce, the effectiveness of leaders and the sustainability of organizational learning cultures in an AI-pervasive world. Finally, the literature also failed to explore how sustained AI use as an offloading tool can ultimately undermine memory, analytical abilities and neural intellectual stimulation or how the habits lead to what is now called digital complacency, i.e. overdependence on technology with loss of alertness and initiative.

Previous studies (Parasuraman and Manzey, 2010) determined that passive use of AI systems leads to a decrease in vigilance but did not explore the effects of passive reliance on AI systems in developmental systems that require human capabilities, nor did it focus on the consequences of attentional failures. The DAM builds on this base in three areas of leadership and organization development practice. First, it redefines complacency as more of a

momentary error risk than a future leadership capability threat as it becomes the culmination of a vicious developmental cycle of neurological deterioration, or neuroplastic decay. Second, it transforms the unit of analysis from the individual operator to the organization system in such a way that anyone who sees it will understand how digital complacency can infiltrate an entire generation of emerging leaders, potentially endangering the sensemaking, the talent pipeline and the learning cultures of the organization that OD practitioners are tasked with sustaining. Third, the DAM proposes a theoretically grounded and empirically testable target for the intervention because it provides a mechanism for the emergence of complacency (skill atrophy), a mechanism that was absent from the previous models of automation.

Accordingly, the current study addresses two research questions of direct relevance to leadership and OD scholars.

- RQ1. Does habitual AI dependency undermine the cognitive capacities such as sensemaking, analytical reasoning and strategic judgment that are foundational to effective leadership in complex organizational environments?
- RQ2. Through what sequential cognitive and behavioral mechanisms (cognitive offloading and skill atrophy) does AI dependency ultimately produce digital complacency, and how does this cascade threaten leadership effectiveness and organizational learning systems?

These questions explicitly position the study at the intersection of cognitive psychology and leadership development, responding to the gap in the literature on long-term cognitive costs of AI integration for leaders and organizations.

Theoretical elucidation

The Distributed Atrophy Model: core assumptions, distinctiveness and hypothesis mapping

The current study is conducted by using the tenet of Distributed Atrophy Model (Jadhav, 2025). In the study, the DAM is considered a sensitizing framework, in that the core propositions of the DAM have been established in a non-peer-reviewed dissertation; however, grounded in and triangulated with peer-reviewed scholarship on cognitive offloading (Risko and Gilbert, 2016), automation-induced complacency (Parasuraman and Manzey, 2010) and disuse-related cognitive decline (Salthouse, 2010). Distributed Atrophy Model (DAM) is based on three key assumptions. First, generative AI is a tightly coupled cognitive extension: humans regularly offload complex cognitive functions like sensemaking, strategic analysis and decision synthesis to AI, and these functions don't happen inside the human brain anymore. Second, delegation is not a one-off affair; it is a habit, i.e. a series of low-effort interactions with AI outputs of high reliability, which reinforce an efficient mode of functioning and gradually replace mental effort. Third, and most importantly for leadership and organizational development, the neuroplasticity principle, "use it or lose it," holds true such that cognitive circuits that are not used will undergo measurable atrophy, diminishing the leaders' reasoning capacities they require to navigate ambiguity, make moral judgments and sustain organizational learning (Parasuraman and Manzey, 2010; Salthouse, 2010). The DAM is conceptually different from the general cognitive offloading theory in two key ways. Traditional cognitive offloading theory considers externalization as a neutral or adaptive process that extends the range of human capacities without necessarily affecting the cognitive system itself and does not account for temporal degradation or developmental effects. DAM, however, is a theory that explicitly suggests a developmental trajectory where external offloading, if sustained, will create a vicious cycle in which performance decay happens more quickly than when performed internally, leading to a decrease in self-efficacy, a decrease in metacognitive monitoring and ultimately digital complacency. Furthermore, DAM is built in a different context than cognitive offloading theory has been developed in that it focuses on leadership and organizational development scholarship and highlights the implications of actions for the quality of sensemaking, strategic initiative and collective capability formation. Hypothesis development is based on the assumptions of DAM mechanism. AI Dependency and Cognitive

Offloading relation is widely talked about by DAM; systematic externalization of cognitive tasks can be seen as the result of regular use of AI, as they share tasks that would have previously required focused internal processes with less effort. Cognitive Offloading and Skill Atrophy relation is also supported in the DAM's neuroplasticity decay mechanism, which explains the progressive degradation of domain-relevant cognitive skills (e.g. analytical reasoning, pattern recognition, strategic sensemaking) because of chronic cognitive offloading. Likewise, the DAM's terminal state: eroded competence and digital complacency relation result in low-vigilance acceptance behavior, without questioning the AI output.

Hypotheses development

AI dependency and cognitive offloading

The overlap of AI dependency, that is, habitual dependence on AI devices to perform cognitive tasks, and cognitive offloading, which can be thought of as externalizing mental processes to lessen internal cognitive load (Shalaby, 2024), has become a research question of critical concern in cognitive psychology and human–AI interaction. The difference between the efficiency of AI tools and with large language models that delegate some tasks (Chen *et al.*, 2024), such as reasoning, memory retrieval and decision-making, synthesized evidence indicates a general pattern of negative cognitive trade-offs, particularly when overly used. The initial research on cognitive offloading assumes that it is an adaptive process based on distributed cognition and external aid that can expand human abilities without causing harm in its moderate form (Risko and Gilbert, 2016). But in AI situations, this changes into dependency as tools are used as default proxies, and not as augmented by design; it becomes substituted by habit.

In theory, the Distributed Atrophy Model is explained and provides a solid theoretical foundation for the relationship between AI dependency and cognitive offloading by emphasizing the dangers of chronic offloading. Generative AI is used as a closely integrated cognitive extension in this model, which allows users to offload tasks and reduce internal effort on a cost-benefit trade-off. Tendency of an individual upon this routine dependency leads to distributed atrophy, a progressive weakening of internal capabilities through lack of use, which is exacerbated by overtrust and less metacognitive monitoring. One notable similarity in the many studies conducted in recent times is that there is a dual aspect of a paradox, i.e. efficiency short-term improvement comes at the expense of internal capacities long-term erosion. The study of Moluayonge (2025) tested the mediating role of offloading between AI usage and critical thinking development. Adaptive judgment, moral reasoning and shared organizational understanding are a few things that have direct consequences when thinking about the relationship between AI dependence and the process of cognitive offloading, especially in the context of leadership and organizational development. Wherever and whenever the use of AI is likely to occur, there is a systemic concern with how the leadership pipeline will be impacted as emerging leaders may lose the habit of cognitive engagement through practice, especially in the context of developing competencies in complex and ambiguous environments.

- H1.* Higher levels of AI Dependency will positively predict greater Cognitive Offloading among leaders and employees.

Cognitive offloading and skill atrophy

The relationship between cognitive offloading and skill atrophy has received more academic interest as organizations and learning systems become more dependent on smart technologies. Cognitive offloading is the idea that internal cognitive processes, including memory, reasoning, calculation and problem structuring, are decomposed and given over to external resources to lessen the cognitive load and mental effort (Risko and Gilbert, 2016). Whereas in initial studies offloading was considered as an adaptation to and efficiency-enhancing strategy

in a distributed cognition system, recent literature indicates that sustained offloading can have long-term side effects on the development of individual capabilities. From a cognitive and organizational learning view, the development of skills occurs by engaging in repetitive inner activities, rehearsal and reflection. When these activities are systematically externalized, the chances of inner adoption become less. It has been empirically proven that those who often hand memory and reasoning tasks show weaker recall, less transfer of learning and less depth of thinking than those who use internal strategies (Barr *et al.*, 2015). The findings indicate that offloading, as a beneficial tool for short-term performance, can impair ongoing activation, which is required to sustain and enhance cognitive skills over time. In technology-saturated settings, especially the ones that are dominated by AI-driven solutions, cognitive offloading turns habitual, as opposed to situational. Studies (e.g. Murphy and Metcalfe, 2025; Risko and Gilbert, 2016) show that individuals get less tempted to think intensively when they perceive offloading tools as correct, quick and available whenever needed resulting in less cognitive persistence and less independence in solving problems. Such change in behavior is consistent with the use-it-or-lose-it rule of thinking, according to which, in the case of inactive skills, the loss of skills slowly occurs (Wilmer *et al.*, 2017). Such erosion in organizational context can be in the form of poor decision quality, poor strategic judgment and excessive use of automated products, especially among younger employees who are more accustomed to handing over their thinking to computers. This deterioration of cognitive abilities due to disuse is defined by the so-called concept of skill atrophy. Although the traditional studies on atrophy of skills concentrated on either physical or procedural skills, the new cognitive studies have taken the concept forward to include intellectual skills where reasoning, critical thinking and solving complex problems are equally at risk of depleting when they are not regularly practiced (Salthouse, 2010). Cognitive offloading is one way to speed up this process with a systematic process of bringing people out of cognitively challenging activities and passive consumption of externally produced solutions. Educational and organizational research indicates that offloading individuals on a regular basis results in a lower level of learning retention, lower level of knowledge transferability and less adaptability in the absence of technological support (Aagaard, 2015; Ward *et al.*, 2017). This is especially worrying in the realms of leadership and professional development where long-term cognitive load and autonomy of judgment are the keys to working in ambiguity and complexity. Based on the Cognitive Offloading Theory, the current article believes that long-term cognitive offloading is a direct precursor to skill atrophy because it decreases the cognitive engagement within the system, the practice and monitoring of the metacognition. The more people are forced to use external systems in carrying out their central cognitive tasks, the less the internal processes involved in the maintenance and upgrading of those skills are used, and the slow process of erosion takes place. Therefore, although cognitive offloading can improve short-term performance, it has long-term developmental costs, which are apparent in the long term as decreased independent performance. In the organizational development context, it is not only a cognitive issue for an individual, but a systemic risk to the learning systems in the organization. If cognitive offloading becomes the first resort for a cohort of leaders, organizations gradually become devoid of the depth of thought, the ability to make sense of the situation and the knowledge-sharing capabilities that are vital to them when it comes to dealing with complexity. With such theoretical arguments and growing empirical research, the hypothesis of the study is the following:

- H2. Cognitive Offloading will positively predict Skill Atrophy, as repeated delegation of cognitive tasks limits internal rehearsal and triggers neuroplastic decline.

Skill atrophy and digital complacency

Skill atrophy (also known as deskilling or cognitive atrophy) and digital complacency, i.e. an extension of automation-induced complacency to everyday digital and AI contexts

(Parasuraman and Manzey, 2010), are two threats in human–AI interaction. In the context of generative AI quickly becoming embedded in professional, educational and decision-making processes. Skill atrophy can be defined as the progressive loss of cognitive, perceptual or domain-specific abilities because of chronic inactivity when that task is assumed by AI, which is in line with the use of it or lose it principle of neuroplasticity. Digital complacency is composed of decreased awareness, excess confidence in automatic deliverables and less-vigilant observation or judgmental awareness, which causes individuals to believe the results produced by AI with no critical appraisal (Alwali *et al.*, 2025; Parasuraman and Manzey, 2010). Recent empirical and theoretical outputs have been synthesized into evidence of such phenomena as interlinked consequences of over-reliance on AI, which can be seen as forming a downward spiral where the perceived benefits of efficiency at first sight cover up the actual cognitive decline in the long run.

Skill atrophy is a documented phenomenon in empirical research in every field. In the medical field, the performance of endoscopists who used AI to detect polyps was impacted, as the criticality of the technology, when disabled and the adenoma detection rates declined significantly, as endoscopists began to act differently and refrain from independent work (Budzyń *et al.*, 2025). According to educational research, i.e. Bastani *et al.* (2025), open access to generative AI (e.g. GPT-4 to solve math problems) can improve performance in the short term but worsen retention, transfer and solving of problems when support is withdrawn, especially among learners and novices. Cognitive effort and critical thinking are self-reported to decrease with the usage of generative AI, being related to overconfidence and ceded expertise (Lee *et al.*, 2025). Greater generalizations emphasize similarities with historical automation (e.g. the degradation of manual flying skills in pilots due to the fact they rely on autopilots), even to the effects of generative AI on reasoning, creativity and judgment (Casner *et al.*, 2014). The youngest users and junior employees seem to be the most susceptible group since forming dependency in the early stages suppresses learning, creates illusions of competence, the perceived mastery in the face of real weaknesses.

Digital complacency makes atrophy worse because it encourages excessive dependence without regulation. Vigilance is replaced by high trust in AI and leads to fewer errors and less metacognition, particularly in trustful systems (Parasuraman and Riley, 1997; Rinta-Kahila *et al.*, 2023). This has become the so-called agency decay, where user complacency in making various complicated decisions turns out to be blind unless gaps are revealed by failures. The most salient theme in the analysis is that of augmentation versus erosion, where in the immediate term, generative AI helps the lower-skilled users, but in the longer term has the potential to homogenize output, homogenize thinking and remove buffers that would allow for deviations or failures. The skill atrophy to complacency relationship is direct and relevant to capability development systems and leadership succession pipelines. An AI-driven problem framing is less likely to elicit a response from a leader whose analytical capacities are weakened by the chronic offloading of decision-making and less likely to catch the leader's attention when there is a strategic anomaly; a leader with a weak analytical ability is less likely to model cognitive engagement for his or her team that will produce an organizational learning risk when complacency becomes normalized.

- H3. Skill Atrophy will positively predict digital complacency, reflected in reduced vigilance, over-trust in AI recommendations and lowered initiative.

Sequential mediation of cognitive offloading and skill atrophy

Prior literature on human–AI interaction significantly explains that AI dependency in performing cognitive tasks generates negative outcomes such as digital complacency due to overtrust, and less usage of cognitive abilities (Parasuraman and Manzey, 2010; Risko and Gilbert, 2016). However, the impact is sequential or through a process. This is a progressive process of downward development, which develops dependency, pushes away offloading,

decreases skill base and leads to complacency through displaced vigilance and diminished surveillance ability (Alwali and Alwali, 2025). Cognitive offloading is supported empirically as a primary mediator between AI dependency and the eventual cognitive losses. To date, analyses involving mediation have persistently demonstrated that negative correlations between frequent AI use and critical thinking, or analytical reasoning or reflective judgment are partially or entirely mediated by offloading (Lee *et al.*, 2025). Habitual AI delegation can be either a cause of poorer higher-order skills (e.g. inference, synthesis) or a cause of reduced vulnerability in younger users or novices, mediated through cognitive fatigue or cognitive inertia, an effect of exercising generative AI in education and work (Khan and Suhluli, 2025). This phase of offloading preconditions the onset of skills decay, i.e. an absence of rehearsal speeds up the decline of expertise domains, which is observed in AI-assisted performance in which experts decline in skills faster than their nonreliant counterparts.

Skill atrophy, in turn, acts as a follow-up mediator that enhances complacency. Chronic nonuse undermines self-efficacy, problem-solving and error-detection skills, and establishes the environment of overdependence without control, which is presented in the form of digital complacency when users are passive recipients of the product as they lose the ability to identify the lack of adequate self-efficacy and awareness of the deficiency (Rinta-Kahila *et al.*, 2023). Likewise, cognitive atrophy paradox frameworks represent nonlinear processes wherein reflective interaction results in development, whereas unquestioning delegation results in dependency, digital complacency and loss of analytical autonomy. Similarities related to the concept of automation (e.g. manual skills of pilots being depleted by autopilot) are also applicable to generative AI, where overtrust replaces caution and hastens the process of atrophy and feedback loop reinforcement that leads to complacencies (Alwali and Alwali, 2025; Casner *et al.*, 2014).

- H4. Cognitive Offloading and Skill Atrophy will sequentially mediate the relationship between AI Dependency and digital complacency, such that AI Dependency influences digital complacency through the chained pathway of offloading followed by atrophy.

Based on the formulated hypotheses, Figure 1 was developed conceptually to illustrate the theoretical framework and the interrelationships among the key variables.

Method

The research article uses a cross-sectional survey design, which is quantitative in nature, to test the relationships between AI dependency, cognitive offloading, skill atrophy and digital complacency in organizational and professional context with specific focus on testing direct effects and serial mediation. The research uses structural equation modeling (SEM), which is appropriate for such kinds of models, several mediators, predictive-based hypotheses and theory testing in management and organization studies (Hair and Alamer, 2022). Covariance-based SEM (CB-SEM), adopted in AMOS, was selected over variance-based (PLS-SEM) approaches because the study is confirmatory and theory-testing in nature, the measurement model is fully reflective, the sample size is adequate for covariance-based estimation and CB-SEM provides the model fit indices required to evaluate the overall theoretical framework (Hair *et al.*, 2017).

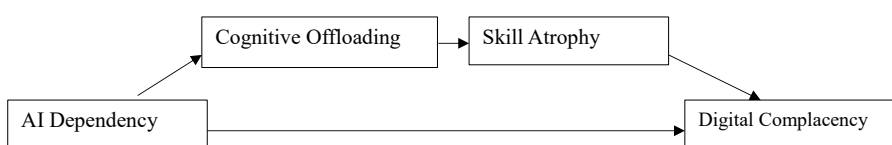


Figure 1. Conceptual framework

Participants and sampling

The participants of the current study are professionals who regularly use generative AI tools in their work. Precisely, these participants were knowledge workers and leaders employed in technology-intensive or AI-adopting organizations. Inclusion criteria required participants to be at least 18 years old, employed full- or part-time, and to report using generative AI applications (e.g. ChatGPT, Copilot or Gemini) at least once per week for work-related tasks such as problem-solving, decision-making, information retrieval, analysis, or report generation. A purposive sampling approach was employed to recruit participants from sectors and roles with high rates of AI adoption. Data collection occurred over three months via online surveys. After screening for incomplete responses, straight lining and multivariate outliers (using Mahalanobis distance), the final useable sample consisted of $n = 303$ participants. This is a sufficiently large sample size to perform SEM with mediation analysis (Hair *et al.*, 2017). The sample was chosen in a purposely heterogeneous way to increase the generalizability to various knowledge-work settings. The participants were predominantly of the age group 25–45 (around 34 years). At the organizational level, 12% were entry-level workers, 48% were mid-level managers and 40% held top leadership positions. The sample was a mixture of several industries with Information Technology (42%), Finance and Banking (14%), Education and Higher Education (42%) and Consulting and Professional Services (2%), operating within Pakistan. Given that a substantial share of respondents was employed in education and higher education, the sample is most accurately characterized as knowledge-intensive, AI-adopting professionals working across technology-intensive and technology-mediated sectors, rather than employees of technology firms exclusively; the framing of the study and its generalizability claims have been aligned with this composition. Every respondent claimed to use generative AI at least once per week and many of them said that they use it every day in their professional activity. The composition encompasses a wide-ranging scope of roles and contexts where AI tools are incorporated in the leadership, decision-making and organizational learning processes. Results can thus be most readily extrapolated to knowledge-based, AI-embracing settings, especially in economies in South Asia and elsewhere emerging and developing.

Measures

Multi-item self-report measures of all constructs based on pre-existing tools and validated in previous AI–human interaction studies were used to measure them. The items were rated using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). All the items were adapted with modification and adding the context of AI. All scales were adapted by replacing generic technology references with explicit references to generative AI tools (e.g. ChatGPT, Copilot, Gemini) and (b) reframing item wording to reflect professional and leadership contexts. Following adaptation, all items were reviewed by a panel of three subject-matter experts in organizational behavior and human–AI interaction for content validity; minor wording adjustments were made based on expert feedback before pilot testing with a convenience sample ($n = 20$ professionals).

The 8-item Artificial Intelligence Chatbot Dependence Scale developed and validated by Zhang *et al.* (2025) was used to measure AI Dependency. The scale has been adapted since the items were reworded from chatbots to AI tools. The scale consists of 8 items for evaluating habitual reliance, preference for AI over independent effort and indispensability. A representative item is “*I rely on AI tools to complete tasks I could otherwise do on my own.*” A 7-item scale is used for measuring cognitive offloading. The items were gathered from the study of Miranda *et al.* (2025). A representative item is “*I use AI tools to store or retrieve information rather than remembering it myself.*” Skill atrophy was measured with seven items drawn from the validated measures of Miranda *et al.* (2025) and Abbas *et al.* (2024). The items were adapted to the context of the present study, with wording revised to reference generative AI tools. Sample item of the scale is “*Since using AI regularly, I feel my*

ability to independently analyze complex problems has declined.” Digital complacency was measured with an 8-item scale adapted from the automation-induced complacency of [Merriitt et al. \(2019\)](#), with reference to “automation” reworded to refer to generative AI output. A sample item is “I tend to accept AI-generated recommendations without critically evaluating them.”

Procedure

The anonymous online survey was facilitated through a secure platform (Google Form) by the participants. They gave informed consent and demographic information, after which they went ahead to fill out the measures in the order that was fixed but randomized to reduce order effects. The questionnaire had attention checks and lasted around 15–20 minutes. The institutional review board granted ethical approval, and the participants were given the freedom to participate voluntarily, with full protection of their data and no deception. To mitigate the potential threat of common method bias, procedural remedies as suggested by [Podsakoff et al. \(2003\)](#) were used and the items were shuffled for careful responses. In addition to that, Harman’s single-factor test was also performed to check for common method bias. The first unrotated factor extracted 42.119% of the total variance, which falls below the 50% threshold. This result, combined with the presence of multiple factors, indicates that common method bias is not a major issue in the dataset.

Data analysis

CB-SEM in IBM SPSS AMOS was used to analyze the data on the basis of covariance. Such a method was selected as it is specifically best suited to theory-testing and confirmatory purposes (enabling the rigorous testing of the hypothesized measurement structure and the suggested sequence of mediational pathways outlined in the Distributed Atrophy Model) ([Hair and Alamer, 2022](#)). CB-SEM in AMOS was used instead of variance-based methods due to the confirmatory nature of the study, the reflective measurement model, the reasonably large sample size ($n = 303$) and the importance of strong global model fit indices to confirm the overall theoretical framework. The measurement model was first assessed with confirmatory factor analysis using a two-step process. First, reliability was measured using Cronbach’s alpha (>0.70) and composite reliability (CR). Second, convergent validity was assessed through indicator loadings (>0.70) and average variance extracted (AVE >0.50). Discriminant validity was established as well. The second phase involved testing the structural model using path coefficients, which were tested using bootstrapping (5,000 subsamples), t -values, p -values (<0.05) and bias-corrected confidence intervals. The overall model fit was evaluated using standard covariance-based indices (CMIN/DF < 3 ; CFI >0.95 ; RMSEA <0.08 ; SRMR <0.08), together with the squared multiple correlations (R^2) of the endogenous constructs. Consistent with the CB-SEM approach, PLS-specific statistics (f^2 effect sizes and blindfolding-based Q^2 predictive relevance) are not required in AMOS and are therefore not reported. Bootstrapped confidence intervals (95%) were applied to test the specific indirect effects in the pathway AI dependency to cognitive offloading and skill atrophy to digital complacency to test the sequential mediation (H4). This methodological framework will allow stringent empirical testing of the hypothesized cascading cognitive processes, which can give solid support to how AI dependence as a habit can compromise leadership-relevant competencies within organizational contexts.

Results

Measurement model

To evaluate the measurement model, it is necessary to check the construct reliability and validity, which is done by observing values of Cronbach’s alpha, CR and AVE ([Hair et al., 2017](#)). To begin with, the factor loadings were analyzed, the measurement model estimates reveal that all the indicator loadings of the current model are in the range and are statistically significant ($p < 0.001$). Therefore, all the items were retained. Secondly, [Table 1](#) revealed that

Table 1. Convergent validity

Construct	CR	AVE	Cronbach's alpha	Item	Standardized loading
Cognitive Offloading	0.976	0.853	0.976	CO1	0.914
				CO2	0.971
				CO3	0.921
				CO4	0.880
				CO5	0.901
				CO6	0.971
				CO7	0.905
Skill Atrophy	0.943	0.675	0.942	SA1	0.824
				SA2	0.867
				SA3	0.816
				SA4	0.873
				SA5	0.837
				SA6	0.847
				SA7	0.823
AI Dependency	0.917	0.582	0.917	AID1	0.743
				AID2	0.764
				AID3	0.803
				AID4	0.767
				AID5	0.840
				AID6	0.771
				AID7	0.741
				AID8	0.664
Digital Complacency	0.897	0.555	0.897	DC1	0.671
				DC2	0.748
				DC3	0.711
				DC4	0.766
				DC5	0.737
				DC6	0.813
				DC7	0.723
				DC8	0.710

Note(s): CMIN = 688.687, DF = 395, CMIN/DF = 1.744, CFI = 0.967, SRMR = 0.050, RMSEA = 0.050

CR and Cronbach's alpha values surpassed 0.70 for every construct, while AVE exceeded 0.50, confirming convergent validity.

Discriminant validity

To obtain discriminant validity, the current research employed the most common techniques of [Fornell and Larcker \(1981\)](#) and the comparison with MSV. AVE of each of the variables exceeds their correlations with the rest of the variables (condition of Fornell–Larcker met). In addition, each construct has much lower values of the MSV than of AVE (maximum MSV = 0.40), which also confirms the discriminant validity. The output does not directly report HTMT ratios, although the trend of low inter-construct correlation is in keeping with reasonable discriminant validity.

Structural model

The first step in the structural model assessment consisted of the identification of collinearity. AI Dependency is the only exogenous construct in the model. As reported in [Table 2](#), its correlations with the endogenous constructs were moderate (0.462 with Skill Atrophy and 0.411 with Digital Complacency). These values remain well below conventional thresholds that would indicate problematic multicollinearity (>0.80 or 0.90). The hypothesis was tested through consideration of the path coefficients (β), their statistical significance (Critical Ratio

Table 2. Discriminant validity

Construct	MSV	MaxR(H)	1	2	3	4
1. Cognitive Offloading	0.281	0.982	0.924			
2. Skill Atrophy	0.400	0.948	0.516***	0.822		
3. AI Dependency	0.214	0.922	0.268***	0.462***	0.763	
4. Digital Complacency	0.400	0.9	0.530***	0.633***	0.411***	0.745

Note(s): *** Correlation is significant at the 0.000 level (2-tailed)

and bias-corrected bootstrap 95% confidence interval with 5,000 resamples) and the total explanatory power of the model. The structural model was also identified with the model fit indices and found an acceptable fit, i.e. CMIN/DF = 1.82, CFI = 0.962, SRMR = 0.050, RMSEA = 0.053. It is important to note that these indices are related to the structural model; on the other hand, measurement model-related fit statistics are also reported in the note to Table 1.

Moreover, the findings of the SEM indicate that there are several important relationships between the constructs. Cognitive Offloading ($\beta = 0.258, p < 0.001$) is influenced by AI Dependency in a significant positive direction, meaning that the higher one is reliant on AI, the more the tendency to offload cognitive tasks is observed. Cognitive Offloading, in its turn, has a highly positive impact on Skill Atrophy ($\beta = 0.491, p = 0.001$), which implies that regular cognitive offloading plays a significant role in the perceived or experienced deterioration in autonomous skill utilization. Skill Atrophy, in turn, illustrates the largest positive direct impact on digital complacency ($\beta = 0.555, p < 0.001$). Besides, AI Dependency has a smaller yet still statistically significant positive direct effect on digital complacency ($\beta = 0.168, p = 0.002$), indicating a smaller yet significant independent effect of AI reliance on digital complacency outside of the mediated relationship. In general, the structural model explains a reasonable amount of variance in Cognitive Offloading (SMC = 0.067), Skill Atrophy (SMC = 0.241) and Digital Complacency (SMC = 0.360) at 6.7 and 24.1 and 36.0%, respectively, which is satisfactory as an explanatory model, especially in the outcome variable. The general results draw attention to AI Dependency as a significant upstream predictor of the suggested chain, and Skill Atrophy has become the most proximate and the strongest predictor of digital complacency. The model explains a significant amount of variability in the outcome (36%), which confirms the theory frame and shows that the relationship between technology reliance and digital outcomes is mainly positive in this setting. The specific indirect effect through the full serial pathway was significant ($\beta = 0.07, 95\% \text{ BC CI } [0.041, 0.112], p < 0.001$). As shown in Table 3, the direct path from AI dependency to digital complacency remained significant ($\beta = 0.168, p = 0.002$), indicating partial serial mediation.

Discussion

The results of the SEM indicate a sequential process by which the dependency on AI creates digital complacency by promoting cognitive offloading and resulting in skills loss. This development indicates that the effectiveness and convenience of AI systems are not cognitively neutral; instead, they are slowly transforming the behavior of users, persuading them to participate in passive and over-dependent interactions with digital technologies.

In line with the cognitive offloading theory (Risko and Gilbert, 2016), AI dependency is closely linked with the externalization of cognitive functions, including memory, reasoning and decision-making. Although offloading can be more efficient in the short term, frequent use of highly reliable AI systems can weaken the incentive for people to perform internal mental activities and create a dependency, which is reinforced. This is indicative of a change in the allocation of cognitive effort whereby the use of external systems becomes a default mode and not a conscious decision.

Table 3. Direct and Mediation path analysis

Hypotheses / Path	Path coefficient (β)	Standardized β	p-value (bootstrap BC)
AI Dependency $\rightarrow$ Cognitive Offloading	0.262	0.258	<0.001
Cognitive Offloading $\rightarrow$ Skill Atrophy	0.55	0.491	<0.001
Skill Atrophy $\rightarrow$ Digital Complacency	0.427	0.555	<0.001
AI Dependency $\rightarrow$ Digital Complacency (direct)	0.147	0.168	0.002
Indirect: AI Dependency $\rightarrow$ Cognitive Offloading $\rightarrow$ Skill Atrophy	0.144 (0.262 $\times$ 0.550)	0.127	<0.001
Indirect: AI Dependency $\rightarrow$ Cognitive Offloading $\rightarrow$ Skill Atrophy $\rightarrow$ Digital Complacency	0.062 (chain product)	0.07	<0.001
Total effect: AI Dependency $\rightarrow$ Digital Complacency	0.209	0.239	<0.001

Note(s): BC = bias-corrected; CI = confidence interval. The indirect effect is significant (BC CI = 0.041, 0.112, $p < 0.001$). $\beta = 0.168$, $p = 0.002$

The results also show that cognitive offloading is a contributory factor to the atrophy of the skills and this goes in favor of the principle of use it or lose it (Ericsson and Lehmann, 1996). Less critical thinking and problem solving reduce the cognitive abilities of individuals with time. Earlier studies on skill degradation caused by automation (Parasuraman and Manzey, 2010; Rinta-Kahila *et al.*, 2023) also point to the fact that the continued dependence on automated systems impairs performance in independent mode. This erosion becomes a significant mediator between dependency and more general outcomes in AI-intensive environments, where tools are widespread.

In turn, skill atrophy is a strong predictor of digital complacency, which is consistent with known views on human-automation interaction. The less competent individuals become, the less capable and motivated they are to challenge or check the output of AI and this contributes to over-trust and lack of vigilance (Parasuraman and Manzey, 2010). This forms a vicious circle where the decreasing skill levels enhance dependency, further undermining critical interaction and encouraging the passive adoption of AI-generated suggestions. This trend is supported by emerging evidence in consumer AI settings (Shin, 2021), as more people become more dependent and less critical of AI systems as time passes.

Interestingly, there is a minor yet important direct impact of AI dependency on digital complacency that implies that complacency can also arise without the decline of skills. Constant communication with AI systems with high reliability can also lead to attitudinal changes, such as overconfidence in the accuracy of the system and less need for human supervision (Lee *et al.*, 2025). This implies that digital complacency is an acquired attitude toward technology as well as an acquired behavioral consequence of cognitive loss.

The results can be added to the body of literature in leadership and organizational development due to the unforeseen cognitive and behavioral outcomes of AI integration. Although AI can lead to greater efficiency, there is a risk that its long-term use can weaken key human abilities and, therefore, the task of organizations is to determine how to balance the technology application with the strategies that would allow maintaining cognitive activity and skill building.

Theoretical implications

The current study contributes to theoretical knowledge by formalizing a serial mediation framework that follows the path of AI dependency to digital complacency due to cognitive and skill-based processes. It connects the different literatures such as cognitive offloading (Risko and Gilbert, 2016), skill atrophy and digital complacency (Parasuraman and Manzey, 2010) to

one comprehensive model, which can be applied to ubiquitous consumer and professional AI. The work narrows in on the concept of skill atrophy as a mediator, demonstrating the fact that the productive distribution of cognition can be achieved, but unbalanced distribution may lead to atrophy instead of extension (Grinschgl *et al.*, 2021).

The pattern of partial mediation is an enhancement to the models of trust calibration (Lee *et al.*, 2025), which hypothesize the presence of both an experiential (direct dependency) and a consequential (atrophy-driven) pathway to the occurrence of complacency. This two-pathway view of human–resource interaction theories can be applied to digital daily life, where complacency might be less evident but more pervasive. Moreover, the incorporation of self-determination theory will help to understand the motivational grounds, i.e. the phenomenon of chronic offloading and subsequent atrophy can be used to undermine perceived competence to promote the process of extrinsic, not intrinsic, dependence on technology (Deci and Ryan, 2008).

In theory, the results put the dichotomous perceptions of AI as empowering or weakening to rest and suggest a contingency model where results are contingent on the relationship between augmentation and delegation. This creates possibilities of theorizing thresholds of adaptive complacency and human–AI symbiosis factors.

The Distributed Atrophy Model offers several implications for leadership development, learning cultures and change management in AI-pervasive organizations. For leadership development, programs must move beyond technical AI literacy to include deliberate cognitive maintenance practices, i.e. structured exercises in unaided strategic sensemaking, scenario planning without AI assistance and metacognitive reflection on one’s reliance on automated outputs. This will help emerging leaders maintain analytical breadth, initiative and moral discernment without allowing their skills to lapse and thereby degrade the quality of their decision-making. Concerning learning cultures, they should seek to codify their learning landscape to ensure that cognitive engagement with a situation is maintained while AI is being used to its full capabilities, such as establishing “AI challenge norms” during team meetings, or conducting regular capability audits tracking measures of situation sensemaking vitality and problem-solving resilience. Lastly, for change management, it is important to recognize digital complacency as a potential risk that is similar to other kinds of complacency that can be found inside an organization. To effectively implement change, approaches should include important safeguards like a gradual rollout of AI usage with intentional friction points, reflective debriefs of decisions supported by AI and specific interventions to strengthen human agency. The model helps with more sustainable technological transformation by tackling these risks proactively, thereby enhancing the long-term capability and effectiveness of the organization’s leadership.

Practical implications

The pathways taken in the study identified and revealed that Educational institutions, organizations and practitioners should adopt a proactive approach to developing policies for the ethical use of AI. To enforce deliberate practice and inhibit atrophy, AI-free exercises should be implemented into educational programs, while metacognitive interventions encouraging AI output verification should be used (Kirschner and van Merriënboer, 2013). These policies can also be applied within organizations. For example, regular skills assessments, human-in-the-loop situations for critical decisions, friction-by-design features and customer involvement can help keep users alert (e.g. delayed AI assistance; Bucinca *et al.*, 2021). Additionally, signs of reflection, source validation and other possible lines of reasoning can be included in the user interface to counter complacent acceptance. Finally, public awareness campaigns should promote balanced AI use as an aid rather than a replacement.

By targeting these interventions, leaders and OD practitioners can break the atrophy pathway. Leadership Development should include a required “AI-free” sensemaking exercise and a metacognitive reflection log that asks participants to reflect strategically without AI.

“Human in the loop” policies for high-stakes decisions along with periodic capability audits to measure independent problem-solving performance can be institutionalized in organizations. HR personnel can establish calibration standards, such as using independent reasoning for novel or ambiguous challenges and relying on AI for routine analytics (Alwali and Alwali, 2025). User interface designers can introduce intentional friction elements (such as “Describe your own thinking before accepting this AI-generated content”). These actions help maintain human agency while augmenting the benefits of AI. At a societal level, the findings further suggest that the efficiency gains offered by AI must be weighed against the risk of a gradual erosion of core human capabilities, underscoring the need for policies that pair AI adoption with deliberate cognitive maintenance and skill-building practices.

Limitations and future research direction

Although informative, the research has shortcomings that indicate the way forward in the research. Self-reported scales can bring about common method bias and reduce understanding of real behavioral complacency; more objective validation would be through experimental paradigms, which include performance measures (i.e. error detection rates in AI-assisted tasks). Cross-sectional data limit causation; longitudinal designs that follow users over longer periods of AI exposure are required to trace how the offloading, atrophy and emergence of complacency vary over time.

The issue of cultural and contextual variability is understudied, such as possibly the pathway may vary between high- and low-AI-adoption societies or professional fields. The issue of moderators (e.g. personality traits, e.g. need for cognition) or the advancement of the task, or transparency of the AI is worth studying. Future research would consider interventions, e.g. literacy training, deliberate practice/mandates or interface nudges, to determine what works. A mixed-methods design that includes qualitative descriptions of lived AI dependency would contribute to the existing knowledge on subjective experiences. Lastly, the framework would be expanded by including consequences on a societal level (e.g. shared vulnerability to AI malfunctions or misinformation).

Conclusion

The current study reveals a dire yet unnoticed threat in the AI era, which is the development of dependency into digital complacency via cognitive offloading and skill atrophy. This path is defined in the study, and it assists in developing a more balanced discussion on the topic of human–AI interaction, where the benefits of augmentation are appreciated, and the dangers that may lead to the propensity of passive and under-vigilant interaction are recognized. Based on the existing knowledge of cognition and skill maintenance and automation interaction, the results call for a change in the paradigm: to see AI as not just the tool but as the determinant of the human cognitive ecology. It must be designed and practiced to produce sustainable integration, i.e. not to deny oneself the possibility to work individually, subject to critical review and to renew skills. As AI continues to enter our lives, we must promote a conscious dependency as opposed to uncritical reliance to keep human agency, strength and adaptive intelligence alive. The work of the future must be based on the foundation of this to develop AI ecosystems that can further develop as opposed to reducing human potential so that technology can be a real companion in cognitive well-being.

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