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When AI Helps but Humans Feel Less Capable: The Impact of Generative AI Reliance on Professional Self-Efficacy and Meaningful Work

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Abstract

While generative artificial intelligence (GenAI) has the potential to enhance knowledge work, the psychological impact of its use is not fully known. Based on Social cognitive theory and Self-determination theory, this study explores whether the use of GenAI erodes employees' professional self-efficacy and subsequently their meaningful work, and whether AI-literacy helps to protect against this negative trend. The three-wave time-lagged survey of 350 knowledge workers in Pakistan was analysed using composite-based regression (PROCESS Model 7) with bootstrapping method, which was cross-validated with PLS-SEM. Professional self-efficacy (β = −.277) and meaningful work (β = −.123) decreased with the dependence on GenAI. Professional self-efficacy was a significant predictor of meaningful work (β = .479) and accounted for half of the total effect (indirect effect = −.133). The indirect effect was reduced when AI literacy was low (−.199), but it became less negative and significant at high AI literacy (−.068; index of moderated mediation = .066). Results were consistent across the control variables, the PLS-SEM and the method-variance checks. The study moves the discussion about GenAI productivity to one about psychological cost, clarifies the role of self-efficacy in the link between reliance and meaningful work and introduces the concept of AI literacy as a trainable organisational shield.

Keywords: Generative AI reliance; professional self-efficacy; meaningful work; AI literacy; knowledge workers

1 Introduction

Generative artificial intelligence (GenAI) tools such as ChatGPT, Copilot, Gemini and Claude

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now draft reports, write code and analyse data for millions of knowledge workers. Their exposure is concentrated in the non-routine cognitive occupations that earlier automation largely spared (Eloundou et al., 2024), and the productivity gains are well documented: GenAI has raised the output of customer-support agents (Brynjolfsson et al., 2025), shortened professional writing time while improving quality (Noy & Zhang, 2023), and helped consultants complete more tasks at higher quality within the technology's capabilities (Dell'Acqua et al., 2023).

Far less is known about how workers experience themselves when a machine performs a growing share of their cognitive labour. This matters because work is a primary source of competence and meaning (Rosso et al., 2010), and meaningful work predicts engagement, commitment and retention (Allan et al., 2019). Automation research has long warned that the more a system takes over, the less operators exercise and trust their own skills (Bainbridge, 1983; Parasuraman & Manzey, 2010). Similar signs are emerging for AI: delegating to AI can impair people's awareness of their own knowledge (Fügener et al., 2021), and knowledge workers who trust GenAI more engage in less critical thinking, whereas those with more self-confidence engage in more (Lee et al., 2025). Cognitive offloading research similarly suggests that outsourcing mental effort to external tools, while efficient, can weaken the internal capacities those tools replace (Risko & Gilbert, 2016). GenAI may thus help employees do more while leaving them feeling less capable.

Social cognitive theory explains why. Self-efficacy is built mainly through mastery experiences—successes attributed to one's own effort (Bandura, 1997). When GenAI produces the analysis or code, success is achieved but no longer clearly owned. Because competence is also a basic psychological need underpinning meaning (Deci & Ryan, 2000; Martela et al., 2018), declining self-efficacy should reduce meaningful work. The effect is unlikely to be uniform, however. Employees with higher AI literacy, understanding of how AI works, where it fails and how to use it (Long & Magerko, 2020; Wang et al., 2023), are more likely to direct and evaluate GenAI than to defer to it.

Three gaps motivate this study. First, research on AI at work has focused on adoption, trust and productivity, leaving its psychological consequences for individual workers underexplored (Budhwar et al., 2023). Second, studies typically measure frequency of use, conflating use with reliance—dependence on GenAI for tasks one would otherwise perform oneself. Third, although scholars argue that AI may threaten meaningful work (Smids et al., 2020; Bankins & Formosa, 2023), the mechanism and its boundary conditions remain untested. Without knowing why and for whom reliance is harmful, organisations have little guidance on how to capture GenAI's benefits while protecting employee motivation. Finally, most evidence comes from Western economies. In emerging economies such as Pakistan, GenAI has spread rapidly through knowledge-intensive sectors, often ahead of formal training or usage policies, making the psychological consequences of reliance both salient and consequential (Budhwar et al., 2023).

We therefore ask whether GenAI reliance reduces meaningful work, whether professional self-efficacy mediates this effect, and whether AI literacy moderates it. The study makes three contributions. It extends social cognitive theory by showing how technology reliance disrupts mastery experiences even when performance improves; it identifies professional self-efficacy as the pathway through which GenAI affects meaningful work, providing empirical grounding for conceptual arguments; and it establishes AI literacy as a trainable boundary condition that determines whether GenAI becomes a substitute for, or a complement to, professional competence. Practically, the study offers organisations evidence-based levers, AI literacy development and mastery-preserving work design, for protecting employee motivation during GenAI adoption. Methodologically, a three-wave design strengthens causal inference relative to the cross-sectional evidence that dominates the field. The remainder of the paper reviews the theoretical background, develops the hypotheses, describes the method and results, and discusses implications, limitations and directions for future research.

2. Theoretical Background

2.1 Social cognitive and self-determination theories

According to social cognitive theory (SCT) (Bandura, 1997), self-efficacy is defined as people's convictions in their capacity to attain specific levels of performance. Bandura (1977) and Gist & Mitchell (1992) identified four sources: mastery experiences, vicarious experiences, verbal persuasion and affective states; mastery is the most potent source only when success is credited to one's own capabilities, but when success is credited to external factors, it is not as potent. The self-efficacy is an interpretation of performance, not the performance itself and so a technology can improve output, but reduce efficacy.

Self-determination theory (SDT) suggests that the satisfaction of autonomy, competence and relatedness needs (Deci & Ryan, 2000; Ryan & Deci, 2017) is essential for wellbeing and motivation. Experience of meaning is a good predictor of competence satisfaction (Martela et al., 2018). In a competent workplace, people are intrinsically motivated and engaged, whereas when this is not the case, their motivation becomes controlled and their wellbeing is reduced (Ryan & Deci, 2017). The two theories are complementary such that SCT helps to understand how competence beliefs are developed and updated, while SDT helps to understand the motivational importance of competence beliefs. They constitute a sequential argument: the use of GenAI affects competence beliefs (SCT), and competence beliefs affect meaningfulness (SDT). This integration is especially well-adapted to GenAI, which directly participates in the cognitive processes in which the knowledge worker demonstrates and exerts their knowledge.

2.2 Core constructs

GenAI reliance is how much an employee relies on GenAI to accomplish work-related tasks, including tasks that they would otherwise do without GenAI. Building on the line of work on automation research, where reliance refers to depending on an aid instead of exercising one's own judgment (Lee & See, 2004), and on the research on AI dependence (Morales-García et al., 2024), reliance is different from use in implying that the person prefers the aid over their own judgment, and that they struggle to work without the tool. For one employee, they can use GenAI on a regular basis to enhance grammar, while for another employee, they can use it less often but rely on it for the very analytical base of their job. Additionally, generated text can be fluent, making its errors less conspicuous and potentially minimizing the impetus to critically evaluate it (Dell'Acqua et al., 2023; Lee et al., 2025). When relying is appropriate, joint performance enhances; when over-reliance occurs, complacency and skill degradation ensue (Parasuraman & Manzey, 2010).

Professional self-efficacy is an employee's belief in their competence to meet the demands of their job (Rigotti et al., 2008). It sits between general self-efficacy and task-specific efficacy, making it broad enough to capture overall professional capability yet sensitive to changes in how work is performed. Because it is continually updated by mastery experiences, it is malleable, making it a plausible channel through which technological change affects psychological outcomes.

Meaningful work is work experienced as significant and purposeful, comprising positive meaning, meaning-making through work and greater-good motivations (Steger et al., 2012). Its drivers include skill variety and task identity (Hackman & Oldham, 1976) and experiences of competence and growth (Rosso et al., 2010). Meta-analytic evidence links meaningful work to engagement, commitment, job satisfaction and performance (Allan et al., 2019), making its erosion a strategic as well as a personal concern. Conceptual work argues that intelligent technologies can either enrich meaningful work by freeing workers for challenging tasks or threaten it by depriving them of opportunities to exercise skill (Smids et al., 2020; Bankins & Formosa, 2023).

AI literacy comprises awareness, usage, evaluation and ethics competencies regarding AI (Wang et al., 2023; Pinski & Benlian, 2024). Awareness concerns recognising AI in the tools one uses; usage concerns applying AI proficiently; evaluation concerns critically assessing AI outputs and choosing appropriate tools; and ethics concerns attending to privacy, misuse and responsibility. AI literacy differs from general digital literacy in its emphasis on how AI generates outputs and on calibrated judgement about when to trust them. It is conceptually distinct from reliance: an

employee may rely heavily on GenAI with high or low literacy. Because it is learnable rather than a fixed trait, it is a practically important boundary condition.

3. Hypotheses Development

3.1 GenAI reliance, professional self-efficacy and meaningful work

Reliance on GenAI should first diminish meaningful work. Skill variety and task identity are core drivers of experienced meaningfulness (Hackman & Oldham, 1976). When GenAI drafts, analyses or codes, it performs much of the activity that previously exercised the employee's skills, shifting their role towards prompting and assembling and shrinking the share of work that bears their own imprint. Reliance also weakens psychological ownership, which arises from investing the self in an object (Pierce et al., 2001); output generated by a machine is less readily felt as one's own. Conceptual work accordingly warns that AI can deprive workers of the achievement and self-development that make work worthwhile (Smids et al., 2020; Bankins & Formosa, 2023). Augmentation may free time for meaningful tasks when GenAI handles peripheral work (Raisch & Krakowski, 2021), but reliance captures dependence for the substantive core of the job: the analytical, creative and judgement-based tasks through which knowledge workers express their expertise. When these tasks are delegated, the employee's contribution becomes harder to see, both to others and to themselves. We therefore expect that, on balance, greater reliance will be associated with a diminished experience of work as significant and purposeful.

H1. GenAI reliance is negatively related to meaningful work.

Reliance should also reduce professional self-efficacy. Mastery experiences build efficacy only when success is attributed to one's own capabilities (Bandura, 1997). When GenAI produces the work, success becomes ambiguous evidence of competence: it is achieved but not owned. Reliance may further erode the underlying skills, as automation research shows that operators who depend on automated aids lose proficiency and confidence (Bainbridge, 1983; Parasuraman & Manzey, 2010), and delegating to AI impairs people's awareness of their own knowledge (Fügener et al., 2021). Reliance also affects the other sources of efficacy. Working alongside a system that produces fluent, fast and apparently expert output invites continuous upward comparison; because the model of competent performance is now a machine that outperforms the employee on speed and breadth, such comparison highlights inadequacy rather than inspiring. Organisational discourse framing GenAI as superior or indispensable may further act as implicit negative persuasion about the value of unaided human capability. As employees come to feel that they could not easily do their work without the tool, their belief in their capacity to meet job demands is likely to decline.

H2. GenAI reliance is negatively related to professional self-efficacy.

Professional self-efficacy should, in turn, foster meaningful work. Competence is a basic need whose satisfaction underpins the experience of meaning (Martela et al., 2018; Ryan & Deci, 2017). Efficacious employees experience work as an arena in which their capacities are exercised and affirmed (Rosso et al., 2010), set more challenging goals and persist longer (Bandura, 1997), producing the sense of progress and growth central to meaning-making (Steger et al., 2012). They are also more likely to believe that their efforts make a difference to others, supporting the greater-good facet of meaningful work. Conversely, employees who doubt their professional competence struggle to see their work as significant, because significance presupposes that one's contribution is real and consequential.

H3. Professional self-efficacy is positively related to meaningful work.

Integrating these arguments, reliance first changes how employees see their own capability, and this changed self-perception colours how meaningful they find their work. This mechanism explains how productivity may rise while the psychological value of work declines: meaningfulness depends not on output alone but on being the competent agent of that output. When reliance separates output from perceived personal capability, gains in productivity need not translate into gains in meaning and may coincide with losses. Because reliance may also affect meaning through task identity and ownership, as argued for H1, we expect partial rather than full

mediation.

H4. Professional self-efficacy mediates the negative relationship between GenAI reliance and meaningful work.

3.2 The moderating role of AI literacy

AI literacy should weaken the effect of reliance on self-efficacy by changing how employees rely on GenAI. AI-literate employees understand how GenAI generates outputs, recognise its tendency to produce plausible errors and can evaluate and refine its outputs (Long & Magerko, 2020; Wang et al., 2023). Even heavy reliance thus involves active engagement—precise prompting, verification and final judgement—which Lee et al. (2025) describe as task stewardship. Because these employees remain authors of the decisions that determine quality, they can attribute success to their own judgement: the locus of mastery shifts rather than disappears. In SCT terms, effective use of GenAI itself becomes a domain in which competence is exercised and demonstrated. Their calibrated trust also prevents uncritical deference to the machine (Lee & See, 2004), consistent with evidence that AI's benefits for creativity depend on the capability of its user (Jia et al., 2024). The contrast is sharp for employees with low AI literacy, who are more likely to experience GenAI as an opaque black box whose outputs they accept rather than direct. Their reliance is passive and substitutive: they neither understand how outputs were produced nor possess the skills to evaluate them, so successes are attributed to the tool and dependence feels like a loss of control. Low literacy may also heighten uncertainty about the adequacy of outputs, and such anxiety, as an affective source of efficacy information, further undermines efficacy beliefs (Bandura, 1997).

H5. AI literacy moderates the negative relationship between GenAI reliance and professional self-efficacy, such that it is weaker when AI literacy is high.

If self-efficacy transmits the effect of reliance to meaningful work and AI literacy weakens the first stage, the indirect effect should also depend on AI literacy, implying first-stage moderated mediation (Preacher et al., 2007; Hayes, 2015).

H6. AI literacy moderates the indirect effect of GenAI reliance on meaningful work via professional self-efficacy, such that the indirect effect is weaker when AI literacy is high.

Figure 1 presents the research model, which corresponds to Hayes' (2022) PROCESS Model 7.

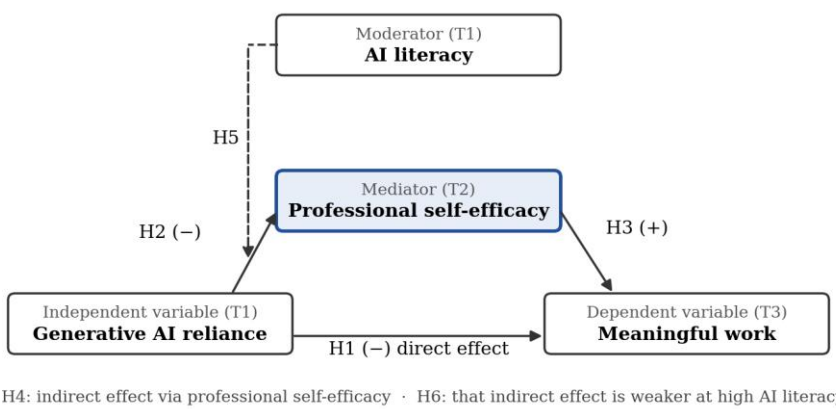


Figure 1. Hypothesized research model

Note. T1–T3 denote the measurement wave. The dashed arrow indicates moderation of the GenAI reliance–self-efficacy path.

4. Methodology

4.1 Research design

Following a positivist, deductive approach, we used a three-wave time-lagged survey. GenAI reliance, AI literacy and controls were measured at Time 1 (T1), professional self-efficacy four

weeks later (T2), and meaningful work four weeks after that (T3). Temporal separation reduces common method bias and establishes temporal precedence, which is particularly important for mediation (Maxwell & Cole, 2007; Podsakoff et al., 2012; Spector, 2019). Four-week intervals are long enough to reduce carry-over effects yet short enough to limit attrition. Self-reports suit these constructs, which are internal states or self-knowledge best known to the focal employee; supervisors have limited access to employees' dependence on GenAI, competence beliefs or experience of meaning.

4.2 Sample and procedure

Participants were knowledge workers in Pakistan's IT/software, banking and finance, telecommunications, consulting, marketing, media and higher-education sectors, where GenAI exposure is concentrated (Eloundou et al., 2024). Studying an emerging economy also responds to the dominance of Western samples in AI-at-work research (Budhwar et al., 2023). Purposive sampling targeted full-time employees with at least one year in their occupation who used GenAI for work at least weekly; screening questions enforced these criteria. Access was obtained through HR departments of participating organisations and supplemented by professional networks and snowball referrals. These sectors were selected because their work is predominantly non-routine and cognitive, and because GenAI use in them is widespread and largely discretionary, producing meaningful variation in reliance. GenAI reliance is how much an employee relies on GenAI to accomplish work-related tasks, including tasks that they would otherwise do without GenAI. Building on the line of work on automation research, where reliance refers to depending on an aid instead of exercising one's own judgment (Lee & See, 2004), and on the research on AI dependence (Morales-García et al., 2024), reliance is different from use in implying that the person prefers the aid over their own judgment, and that they struggle to work without the tool. For one employee, they can use GenAI on a regular basis to enhance grammar, while for another employee, they can use it less often but rely on it for the very analytical base of their job. Additionally, generated text can be fluent, making its errors less conspicuous and potentially minimizing the impetus to critically evaluate it (Dell'Acqua et al., 2023; Lee et al., 2025). When relying is appropriate, joint performance enhances; when over-reliance occurs, complacency and skill degradation ensue (Parasuraman & Manzey, 2010).

Respondents (54.6% male) were mostly aged 25–34 (50.0%), held master's degrees (51.4%) and middle-level positions (52.9%), and averaged 8.94 years of experience (SD = 6.09). IT/software (23.1%) and banking/finance (18.9%) were the largest sectors; 78.6% used GenAI daily or several times a week.

4.3 Measures

All items used five-point Likert scales (1 = strongly disagree, 5 = strongly agree) and were averaged into composites (Table 1). Because no established scale measures workplace reliance on GenAI, seven items were adapted from Morales-García et al.'s (2024) unidimensional AI dependence scale and extended to reflect the substitution, default and dependence features of reliance (Lee & See, 2004). Items referred to work tasks and named common tools (e.g. ChatGPT, Copilot, Gemini, Claude), and covered depending on GenAI to complete tasks, turning to it first, using outputs with little modification and difficulty working without it. AI literacy used Wang et al.'s (2023) 12-item scale covering awareness, usage, evaluation and ethics, averaged into an overall score because the hypotheses concern overall literacy. Professional self-efficacy used Rigotti et al.'s (2008) six-item short occupational self-efficacy scale, and meaningful work used the ten-item Work and Meaning Inventory (Steger et al., 2012), whose total score indexes overall meaningful work. Four reverse-worded items were recoded. Following Bernerth and Aguinis (2016), we controlled for age, gender, education, work experience and frequency of GenAI use, the last to separate reliance from exposure.

Table 1. Measurement instruments

Construct	Source	Items	Wave	Sample item
GenAI reliance	Adapted from Morales-García et al. (2024)	7	T1	"I find it difficult to complete my work tasks without generative AI."
AI literacy	Wang et al. (2023)	12	T1	"I can evaluate the capabilities and limitations of an AI application or product after using it for a while."
Professional self-efficacy	Rigotti et al. (2008)	6	T2	"Whatever comes my way in my job, I can usually handle it."
Meaningful work	Steger et al. (2012)	10	T3	"I have found a meaningful career."

4.4 Analytical strategy

Data were screened for missing values, outliers and straight-lining; no missing data remained in the matched sample, and skewness and kurtosis were examined to assess normality. The measurement model was then assessed through confirmatory composite analysis (Hair et al., 2020): loadings ≥ .708, Cronbach's alpha and composite reliability ≥ .70, AVE ≥ .50, and HTMT < .85 (Henseler et al., 2015; Hair et al., 2019). Common method bias was examined with Harman's test, full-collinearity VIFs (Kock, 2015) and the correlational marker technique (Lindell & Whitney, 2001). The structural model was estimated with OLS regression on standardised composites following PROCESS Model 7 (Hayes, 2022). Indirect and conditional indirect effects and the index of moderated mediation were tested with 10,000 percentile bootstrap resamples (Hayes, 2015; Zhao et al., 2010); interactions were probed with simple slopes and the Johnson–Neyman technique. Composite-based regression was chosen because the hypotheses concern relationships among overall constructs measured with well-established scales, and because the conditional process framework provides direct tests of conditional indirect effects; percentile bootstrapping avoids distributional assumptions about indirect effects, which are typically non-normal (Preacher et al., 2007). Robustness checks included control variables, PLS-SEM re-estimation with a two-stage interaction term (Becker et al., 2018; Hair et al., 2022), a Gaussian copula endogeneity test (Park & Gupta, 2012) and dimension-level moderation.

4.5 Ethical considerations

The study was approved by [name of institution]'s research ethics committee [approval reference]. Participation was voluntary and anonymous, informed consent was obtained at each wave, and organisations received only aggregated results.

5. Results

5.1 Measurement model and common method bias

Table 2 shows that construct means clustered near the midpoint, with skewness and kurtosis within ±1. Cronbach's alpha (.887–.942) and composite reliability (.912–.950) exceeded .70, and AVE (.597–.674) exceeded .50. One loading (.698) fell marginally below .708 but was retained because removal did not materially improve reliability or AVE (Hair et al., 2022). Discriminant validity was supported: each construct's square root of AVE exceeded its correlations, and all HTMT ratios were below .85 (Table 3). The highest ratio (.558), between self-efficacy and meaningful work, is theoretically expected yet still indicates clear empirical distinctiveness. Notably, GenAI reliance and AI literacy were only weakly correlated (r = .092), supporting their treatment as distinct constructs.

Table 2. Descriptive statistics, reliability and convergent validity

Construct	Mean	SD	Skew.	Kurt.	α	CR	AVE	Loadings
GenAI reliance (GAR)	3.011	.912	.017	−.788	.887	.912	.597	.698–.814
AI literacy (AIL)	3.026	.947	−.032	−.689	.942	.950	.613	.728–.837

Construct	Mean	SD	Skew.	Kurt.	α	CR	AVE	Loadings
Professional self-efficacy (PSE)	3.015	1.009	−.032	−.811	.903	.925	.674	.774–.844
Meaningful work (MW)	3.059	.932	.027	−.611	.926	.938	.602	.729–.815

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Table 3. Discriminant validity

Construct	GAR	AIL	PSE	MW
GAR	**.773**	.106	.283	.269
AIL	.092	**.783**	.199	.095
PSE	−.253	.184	**.821**	.558
MW	−.244	.086	.510	**.776**

Note. Bold diagonal = square root of AVE; below diagonal = correlations; above diagonal = HTMT ratios.

Common method bias was unlikely. The first unrotated factor explained 25.30% of variance (below 50%), and full-collinearity VIFs ranged from 1.057 to 1.434 (below 3.3; Kock, 2015). Using the smallest positive correlation (r = .086) as a marker (Lindell & Whitney, 2001), all theoretically relevant correlations remained significant after adjustment (e.g., GAR–PSE r = −.371; PSE–MW r = .464). Inner VIFs (1.010–1.068) indicated no collinearity.

5.2 Hypothesis testing

GenAI reliance was negatively related to meaningful work (β = −.123, p = .010) and professional self-efficacy (β = −.277, p < .001), supporting H1 and H2 (Table 4; Figure 2). Professional self-efficacy strongly predicted meaningful work (β = .479, p < .001, f^2 = .296), supporting H3. AI literacy was also positively related to self-efficacy (β = .222, p < .001). The model explained 12.4% of the variance in self-efficacy and 27.5% in meaningful work, with positive out-of-sample Q^2predict values (.095 and .263), indicating predictive relevance (Shmueli et al., 2019). The modest R^2 for self-efficacy is expected, because self-efficacy is shaped by many factors beyond technology use, such as training, feedback and past performance (Bandura, 1997).

Table 4. Structural model results

Hyp.	Path	β	SE	t	p	95% CI	f^2	Decision
H1	GAR → MW	−.123	.047	−2.599	.010	[−.216, −.030]	.019	Supported
H2	GAR → PSE	−.277	.051	−5.483	< .001	[−.377, −.178]	.087	Supported
H3	PSE → MW	.479	.047	10.142	< .001	[.386, .572]	.296	Supported
—	AIL → PSE	.222	.051	4.376	< .001	[.122, .322]	.055	—
H5	GAR × AIL → PSE	.138	.053	2.604	.010	[.034, .241]	.020	Supported

Note. Standardized OLS coefficients on composite scores. R^2 = .124 (PSE) and .275 (MW).

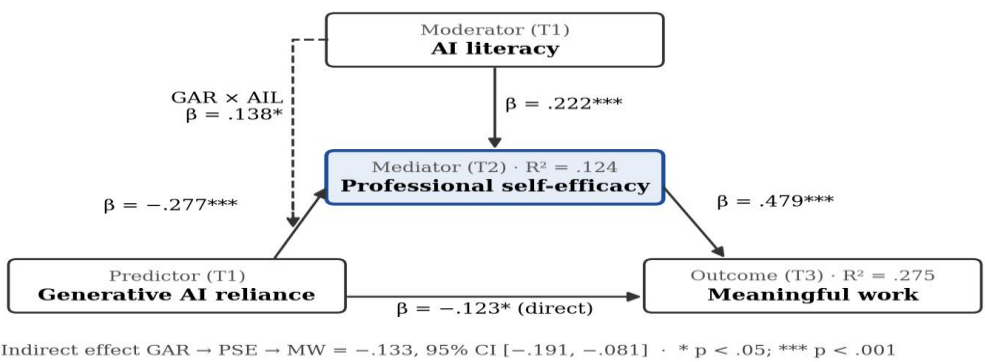


Figure 2. Structural model with standardised path coefficients

The indirect effect of reliance on meaningful work through self-efficacy was significant (−.133,

95% CI [−.191, −.081]), supporting H4 (Table 5). Because the direct effect remained significant, mediation was complementary and partial (Zhao et al., 2010), with the indirect path accounting for 52% of the total effect.

The GAR × AIL interaction was positive and significant (β = .138, p = .010), supporting H5; its small effect size (f^2 = .020) is typical of field interactions (Aguinis et al., 2005). The negative slope was steepest at low AI literacy (β = −.415, p < .001), significant at the mean (β = −.277, p < .001), and marginal at high AI literacy (β = −.140, p = .052) (Figure 3). The Johnson–Neyman analysis showed that the effect was significant for 81.4% of respondents, becoming non-significant only above 0.99 SD above mean AI literacy.

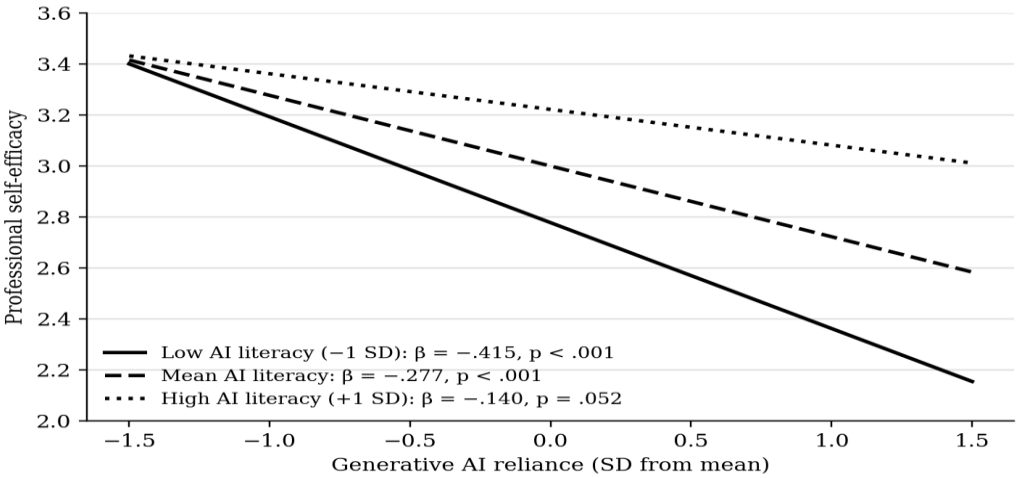


Figure 3. Simple slopes of GenAI reliance on professional self-efficacy at three levels of AI literacy

Supporting H6, the conditional indirect effect weakened from −.199 at low to −.133 at mean and −.068 at high AI literacy, and the index of moderated mediation was significant (.066, 95% CI [.016, .116]). The indirect effect remained significant even at high AI literacy, although it was roughly two-thirds smaller than at low literacy, indicating that AI literacy attenuates rather than eliminates the competence-mediated cost of reliance.

Table 5. Mediation, moderation and moderated mediation

Effect	AI literacy	Estimate	SE	95% CI / p
Indirect effect GAR → PSE → MW (H4)	—	−.133	.028	[−.191, −.081]
Conditional effect GAR → PSE (H5)	Low (−1 SD)	−.415	.074	p < .001
	Mean	−.277	.051	p < .001
	High (+1 SD)	−.140	.072	p = .052
Conditional indirect effect (H6)	Low (−1 SD)	−.199	.041	[−.282, −.122]
	Mean	−.133	.028	[−.191, −.081]
	High (+1 SD)	−.068	.035	[−.137, −.002]
Index of moderated mediation (H6)	—	.066	.026	[.016, .116]

Note. Confidence intervals are 95% percentile bootstrap intervals (10,000 resamples).

5.3 Robustness checks

The results were robust (Table 6). Adding controls left all estimates virtually unchanged, and no control was significant. PLS-SEM re-estimation with the path weighting scheme produced nearly identical paths and equivalent measurement properties (AVE = .596–.674; CR = .911–.950), so the findings do not depend on unit weighting of indicators. All four AI literacy dimensions significantly moderated the reliance–self-efficacy link (awareness β = .118; usage β = .128; evaluation β = .106; ethics β = .137; all p < .05), indicating a broad-based buffer. The Gaussian copula test was inconclusive because the composites did not depart sufficiently from normality

for copula terms to be identified (Becker et al., 2022); endogeneity is therefore acknowledged as a limitation.

Table 6. Robustness of key estimates

Estimate	Baseline	With controls	PLS-SEM
GAR → PSE	−.277***	−.277***	−.289***
AIL → PSE	.222***	.221***	.226***
GAR × AIL → PSE	.138*	.137*	.133*
GAR → MW	−.123*	−.125*	−.118*
PSE → MW	.479***	.477***	.483***
Indirect effect	−.133 [−.193, −.081]	−.132 [−.193, −.080]	−.139 [−.198, −.088]
Index of moderated mediation	.066 [.017, .118]	.065 [.017, .117]	.064 [.016, .116]

Note. * p < .05; *** p < .001. Brackets show 95% bootstrap CIs; baseline intervals differ from.

6. Discussion

This study explores whether the use of GenAI by knowledge workers comes with a psychological cost, which has thus far been ignored in productivity research. All six of the hypotheses were supported and the results proved to be stable when tested with the control variables, and when tested with alternative estimation method and method-variance adjustments. Self-efficacy mediated around 50% of the effect of GenAI reliance on lower professional self-efficacy and meaningful work; and AI literacy reduced the direct effect and the mediation effect. While GenAI can help them do more, the more they use it, the less they feel capable and the less impact it has on their work.

The effect of reliance on self-efficacy (β=−.277) was almost double that of its direct effect on meaningful work, indicating that the immediate psychological impact of reliance is related to how employees perceive themselves to be performing. This is a continuation of the research showing that trust in GenAI and self-confidence do not always go together (Lee et al., 2025), and that AI delegation can lead to less metaknowledge (Fügener et al., 2021); this finding suggests that the effects of trust and self-confidence at the task level seem to add up to a reduction in self-confidence at the occupational level. The outcomes are in line with, and do not contradict, productivity studies (Brynjolfsson et al., 2025; Noy & Zhang, 2023): An employee can be objectively more productive, and subjectively less capable. This disconnect is significant because self-efficacy is the key factor in determining goals, effort, and perseverance in the face of failures (Bandura, 1997). Therefore, the gains in productivity that come with compromising self-efficacy could prove volatile, especially if the employees are assigned to tasks that are not within the scope of GenAI's capabilities (Dell'Acqua et al., 2023) and require a different set of skills and confidence that has not been put to use.

As is predicted by SDT, meaningful work was the most robust predictor of self-efficacy (f^2 = .296), which was the component that would influence meaning through competence. Work is seen as a place for people to demonstrate and be validated as they feel they are able to meet the demand of the job. The other half of the total effect came from the residual direct effect which refers to other ways of complementing the competence pathway (i.e., reduced task identity and skill variety (Hackman & Oldham, 1976) and weaker psychological ownership of outputs produced to a large extent by a machine (Pierce et al., 2001)). While AI literacy prevented the harm, it was not enough to remove reliance: 81.4% of respondents who were high level in AI literacy were still harmed by reliance. These findings are supported by the Pakistani context. The adoption of GenAI in the sampled sectors has been largely driven by the employees themselves and there is little indication of any formal training, meaning many workers are using GenAI without the protection of appropriate literacy. Notably, the correlation between AI literacy and reliance was very low (r = .092) meaning that non-reliance wasn't a result of being literate, but rather, AI literacy seems to shift the nature of reliance rather than the amount of reliance. The protection was identical across all four literacy dimensions, indicating a lack of a single skill, and a more general understanding of AI. This matches the theory that AI-literate workers actively engage, prompting accurately,

verifying and integrating outputs with their own, and thus claiming the authorship of the outcome (Lee et al., 2025). Self-efficacy also experienced a positive main effect of AI literacy, indicating that skills in working with AI have become part of what employees consider professional skills.

6.1 Theoretical implications

First, the study extends SCT to a human–AI collaboration setup where reliance serves as a state in which success and self-efficacy are separated. Our results indicate that success in classic SCT leads to experiences of mastery; however, when an intelligent tool co-produces success, success is attributionally ambiguous, which is contrary to classic SCT. Given that the assistance provided by GenAI is cognitive, and cannot be easily distinguished from the contribution of the worker, the principle that externally aided success leads to little efficacy (Gist & Mitchell, 1992) can be said to apply with a certain intensity. As opposed to the calculator or template, GenAI's output of argumentation, interpretation or solution is judgement-like, representing what knowledge workers consider the true heart of their knowledge. The study of technology mediated work should also examine not only the benefits of technology on work performance, but how technology changes the nature of the attributions that make up that performance as evidence of capability.

Second, the study offers empirical support for conceptual arguments that AI will be a threat to meaningful work (Smids et al., 2020; Bankins & Formosa, 2023) by articulating the mechanism of professional self-efficacy. It demonstrates that the SDT link between competence and meaning remains when competence threat is not from the supervisor but from technology. The importance of this integration lies in the fact that the literature of meaningful work has been largely focused on job characteristics and leadership as antecedents of meaningfulness; our work extends this list by introducing the human–technology relationship and demonstrates that this relationship has an impact on meaning partly through self-concept.

The moderation findings also clarify SCT's depiction of the changes in efficacy beliefs that occur with new tools. The impact of GenAI is not to lessen ability, but to shift distributions of ability. The skills of directing, verifying and integrating AI outputs open up a new space for mastery experiences for AI-literate employees, while it does not provide mastery experience for employees who are not AI-literate. As such, one needs to consider the ability to use intelligent tools as an emerging professional competence, as per the self-efficacy theory.

Third, the results place the automation–augmentation paradox (Raisch & Krakowski, 2021) on the individual psychology level. When GenAI is used as augmentation, it works psychologically like automation when employees use it for the primary part of their work, indicating that the difference is more about how it is used, rather than the technology.

This study recasts AI literacy as a psychological resource, beyond a simply performance-oriented concept (Long & Magerko, 2020; Pinski & Benlian, 2024), and categorizes the degree of reliance as either active or evaluative reliance or passive and substitutive reliance. Since the association of AI literacy with reliance was almost independent, the protection provided by AI literacy could not be attributed to the fact that literate employees rely less. Theories about human-AI collaboration should thus be founded in understanding how much and not just how employees use AI. Last, the study tests reliance as a separate and important construct, as there was some substantial variation in reliance even within a sample of regular users, and reliance predicted outcomes even after controlling for frequency of use.

6.2 Practical implications

The results have significant implications for organisations aiming to reap the rewards of GenAI, while maintaining the motivation of their employees. Organisations should view GenAI literacy training as a foundational part of their GenAI adoption, not an optional extra; the only factor in this model that increased self-efficacy directly, and decreased reliance costs. The effect was mitigated by all four dimensions, so programmes should focus on building understanding of how GenAI produces outputs, skills in how to use it, verification and critically evaluating outputs, and awareness of ethical risks – with a focus on employees with low literacy, who exhibited the

greatest decline.

Second, managers need to create tasks to maintain mastery experiences (Parker & Grote, 2022), as self-efficacy is related to attributed successes. Some practical things include having employees write out their thoughts or suggestions with or without the help of GenAI, not doing high-judgement tasks with GenAI, and swapping tasks to ensure that important skills are practiced. Thirdly, human contribution needs to be made visible in performance feedback by acknowledging the judgement and quality control a human intervention adds to the outputs of AI, and by avoiding stories about GenAI as a replacement for expertise, which serves as negative verbal persuasion.

Fourth, HR activities should assess self-efficacy and meaningful work in addition to productivity indicators because those indicators can mask a decrease in motivation associated with turnover (Allan et al., 2019). Early career people are perhaps the most likely to benefit from GenAI in terms of productivity (Brynjolfsson et al., 2025) but also to need to develop confidence and self-efficacy in the early stages of their careers; onboarding should help these employees develop some initial skills and confidence to use GenAI in the future. For emerging markets like Pakistan, where the use of GenAI may have already started before the official regulations are in place, adopting these practices can be incorporated into AI usage policies from the beginning. Fifth, organisational AI policies ought to strive for appropriate use, rather than maximum use, of GenAI – that is, tasks that benefit from GenAI should be complemented with tasks that would benefit from humans, and ensure that access to GenAI is accompanied by expectations of verification and accountability. Lastly, employees can design their own use of GenAI (Wrzesniewski & Dutton, 2001) and take on peripheral or routine tasks while also owning the work that is created that expresses their expertise and provides their work with meaning. When employees are reflecting on what tasks they wish to continue to take on themselves, they can use GenAI to enhance the tasks they take on, not replace them.

6.3 Limitations and future research

Several limitations qualify the findings and suggest directions for future research. First, although the time-lagged design established temporal precedence, each construct was measured once, so reverse causality cannot be excluded: employees with low self-efficacy may rely more on GenAI to compensate. The copula test was also inconclusive. Cross-lagged panel designs and experiments manipulating reliance could test reciprocal, potentially self-reinforcing effects. Second, all measures were self-reported; usage logs and performance-based AI literacy tests would strengthen future work, and experience sampling could capture daily within-person dynamics. Third, the reliance scale was adapted from a student measure (Morales-García et al., 2024) and needs validation across occupations and cultures. Fourth, the single-country, purposive sample limits generalizability. Cultural values such as power distance and collectivism may shape how employees interpret AI assistance and attribute success, so cross-cultural comparisons are needed to establish whether the pattern observed in Pakistan generalizes to other institutional contexts, to non-knowledge work and to organisations with mature GenAI policies. Fifth, the modest R^2 for self-efficacy (.124) indicates other influences, and task characteristics, such as whether tasks fall inside GenAI's capability frontier (Dell'Acqua et al., 2023), were not measured. Finally, meaningful work was modelled as an overall construct, so we cannot identify which of its facets is most affected, and the three-item AI literacy subscales limit the precision with which the dimensions' unique contributions can be separated.

Beyond addressing these limitations, future research should examine further mediators that may explain the residual direct effect, such as psychological ownership, perceived task identity, autonomy, authenticity and skill-obsolescence anxiety. Boundary conditions deserve attention at several levels: career stage and expertise at the individual level, because novices may gain most in productivity but lose most in mastery; task complexity at the task level; and AI leadership, organisational AI policies, psychological safety and learning climate at the team and organisational levels. Researchers should also examine AI literacy dimensions with performance-based measures, since our expectation that evaluation skills would matter most was not borne out.

Downstream outcomes, including engagement, creativity, turnover intentions, career adaptability and long-term skill retention, would clarify the organisational costs of unmanaged reliance. Finally, intervention studies could test whether AI literacy training, mastery-preserving work design or recognition of human contribution reduce the psychological costs identified here.

7. Conclusion

The productivity gains of generative AI are now well established, and it's quickly becoming a part of knowledge workers' daily routines. That psychological price may not be so obvious, according to this study. This study presents three-wave data collected from 350 knowledge workers and demonstrates that the reliance on GenAI decreases professional self-efficacy, which in turn impacts meaningful work, both directly and indirectly through a reduction in professional self-efficacy. This study reveals that reliance on GenAI negatively impacts professional self-efficacy and, through that, meaningful work directly, and indirectly, through the impact of GenAI on the decrease in self-efficacy, with three-wave data collected from 350 knowledge workers. This suggested that the protection of employees who rely on GenAI seemed to be related to how they do so: as a "directive, not a passive recipient." For organisations, the question is, "What do employees do with GenAI, and how will it affect their feeling of being competent professionals working on things that matter? Organisations are thus not asking about the use of GenAI at all, or whether they use it much, but are asking how they are going to use it so that it doesn't diminish the notion of employees being competent professionals doing something that matters. To truly leverage the potential of GenAI to help with productivity, organizations must work to ensure that their workforce remains human-centric by valuing and safeguarding mastery and bringing human input to the forefront, as this is the key to achieving the benefits of AI literacy. Hence, sustainable human–AI collaboration requires that humans do not feel overwhelmed by AI.

Declarations

Author Contributions

Muhammad Usman Siddqiue and Syed Ali Sultan contributed to the conceptualization, research design, methodology, data collection, data analysis, interpretation of findings, and preparation of the manuscript. Both authors contributed to writing—original draft and writing—review and editing. Both authors read and approved the final version of the manuscript.

Data Availability Statement

All relevant data generated or analysed during this study are included within the article. No additional data is available from the corresponding author.

Conflict of Interest Statement

The author declares that there is no conflict of interest regarding the publication of this paper.

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Use of Generative AI

Use of Generative AIL The authors declare that no generative artificial intelligence tools were used to conduct the literature review, generate the scholarly content, interpret the evidence, or formulate the conclusions presented in this article.

Informed Consent

Participation was voluntary and anonymous, and informed consent was obtained from all participants at each wave.

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Appendix A. Generative AI Reliance Scale (adapted)

Items were rated on a five-point scale (1 = strongly disagree, 5 = strongly agree) and adapted from Morales-García et al. (2024). Instructions referred to generative AI tools used for work (e.g. ChatGPT, Copilot, Gemini, Claude).

Code	Item
GAR1	I rely on generative AI tools to complete my work tasks.
GAR2	I find it difficult to complete my work tasks without generative AI.
GAR3	When I face a work problem, I turn to generative AI first.
GAR4	I depend on generative AI to generate ideas for my work.
GAR5	I use generative AI outputs in my work with little or no modification.
GAR6	I feel uncomfortable when I cannot access generative AI at work.
GAR7	I now use generative AI for tasks I previously did on my own.

Note. The remaining scales were used as published: AI literacy (Wang et al., 2023), professional self-efficacy (Rigotti et al., 2008) and meaningful work (Steger et al., 2012). Reverse-coded items were AIL2, AIL5, AIL11 and MW3.