



THE EMPOWERMENT–ENTRAPMENT PARADOX OF GENERATIVE AI IN  
ENTREPRENEURSHIP: DIMINISHING RETURNS OF GENAI USE FOR ENTREPRENEURIAL  
JUDGMENT AND VENTURE PERFORMANCE

Ayesha Anzer <sup>1</sup>, Noman Iqbal <sup>2</sup>, Afaque Ahmed <sup>3</sup>, Mian Haseeb Mushtaq <sup>4</sup>

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**Affiliations:**

<sup>1</sup> University of Regina, Regina,  
Saskatchewan, Canada  
Email: [aag833@uregina.ca](mailto:aag833@uregina.ca)

<sup>2</sup> Golden Gate University,  
San Francisco, California, USA  
Email: [niqbal@my.ggu.edu](mailto:niqbal@my.ggu.edu)

<sup>3</sup> Director, MedicPro International  
Academy Ltd. United Kingdom  
Email: [drafaqueahmedmangi@gmail.com](mailto:drafaqueahmedmangi@gmail.com)

<sup>4</sup> Department of Software Engineering,  
Lahore Garrison University, Pakistan  
Email: [haseebmuhstaq@gmail.com](mailto:haseebmuhstaq@gmail.com)

**Corresponding Author's Email:**

<sup>1</sup> [aag833@uregina.ca](mailto:aag833@uregina.ca)

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**Abstract**

Generative artificial intelligence (GenAI) is rapidly transforming entrepreneurial practice, but its implications for founders' decision-making capabilities are not well understood. The study examined the nonlinear relationship between the intensity of GenAI use and entrepreneurial judgment quality and the subsequent relationship between judgment quality and new venture performance. Drawing on cognitive offloading theory and entrepreneurial judgment under uncertainty, we argue that GenAI initially provides cognitive augmentation but its marginal association with judgment quality diminishes as usage intensifies. We use two-wave survey data from 212 technology venture founders who adopted GenAI, and estimate hierarchical polynomial regressions with HC3 heteroskedasticity-consistent standard errors. Results suggest a significant concave association between intensity of GenAI use and quality of entrepreneurial judgment ( $b = -0.09, p < 0.05$ ), consistent with diminishing marginal returns, but because the estimated extremum falls outside the observed 1–7 range and the upper-bound slope is not significantly different from zero, these data do not establish a full inverted-U relationship within the range of GenAI use observed. Entrepreneurial judgment quality is positively associated with venture performance ( $b = 0.29, p < 0.001$ ), though because judgment and performance were measured concurrently, this association should not be interpreted causally. Founder technical expertise is associated with a significantly weaker negative curvature ( $X^2 \times W: b = 0.09, p < 0.05$ ), suggesting technical expertise may buffer against diminishing returns at high usage, though this interaction should be interpreted with caution given the sample's limited power to detect small interaction effects. Conditional indirect associations through judgment quality decline with increasing GenAI use and are weakest among low-expertise founders, becoming marginally negative though not statistically significant at the highest usage levels. The findings suggest that the entrepreneurial value of GenAI depends not simply on adoption but on the extent to which intensive use is integrated with independent human judgment.

**Keywords:** Generative Artificial Intelligence; Entrepreneurial Judgment; New Venture Performance; Empowerment–Entrapment Paradox; Technical Expertise; Nonlinear Effects; Entrepreneurship.

**1. Introduction**

Generative artificial intelligence (GenAI) has become a groundbreaking technology for entrepreneurship and has rapidly become a transformative technology. Modern GenAI tools that can create text, code, images, business analyses, and strategic recommendations empower founders to do tasks that used to take years of expertise, hours of work, or huge budgets. These skills could make it more accessible for people to access entrepreneurial resources and broaden the scope of entrepreneurial activities that can be undertaken (Nambisan, 2017 and Shepherd & Majchrzak, 2022). However, GenAI gives rise to a basic



paradox: the same capabilities that expand entrepreneurial opportunity can also erode the independent judgment that opportunity exploitation requires. The technology that enhances entrepreneurial cognition can also create the cognitive reliance and undermine the judgment of entrepreneurs (Risko & Gilbert, 2016; Dell'Acqua et al., 2023). GenAI outputs can be highly fluent, coherent, and convincing, but may lack context or specificity, or be incomplete given certain market realities (Madjdi & Wurth, 2026; Rady et al., 2026). This poses an epistemic dilemma for entrepreneurs who are in Knightian uncertainty where there is incomplete information and there are no clear predictions of outcomes (Knight, 1921; Foss & Klein, 2012), for this technology can increase the potential for the lack of independent evaluation.

This two-sidedness of GenAI in entrepreneurship is now starting to be documented in recent scholarly research. Research shows that GenAI can help speed up the process of ideation and venture development (Cao & Bhatia, 2025), but can also lead to overconfidence, lack of differentiation (Impink & Wright, 2025), and diminishing competitive moats (Kovács, 2026). While some recent studies have started investigating nonlinear and curvilinear relationships between GenAI and entrepreneurship (Duong et al., 2026), there is little evidence directly exploring whether usage of GenAI is related to founders' own entrepreneurial judgment in a nonlinear or curvilinear manner. To fill this gap, we ask: How does the intensity of GenAI relate to the quality of entrepreneurial judgment, and how does the link between these factors affect the performance of ventures? Based on the empowerment–entrapment perspective and cognitive offloading theories, we hypothesize that the relationship between the intensity of GenAI usage and entrepreneurial judgment quality is non-linear. In low to moderate usage, GenAI supports entrepreneurial thinking by increasing information gathering, brainstorming possibilities, and speeding up experimentation and alleviating mundane mental processing. High usage, however, can reduce the independent evaluation ability, resulting in poorer judgement. We also believe that this is a significant boundary condition that allows the founders to critically assess the outcomes of AI and keep their own judgment even when using AI intensively.

We employ two-wave survey data on 212 founders of technology-based ventures that use GenAI to test these propositions. Our research has three contributions towards entrepreneurship and AI research. To begin, we offer proof of a concave nonlinear connection between the intensity of GenAI use and entrepreneurial judgment quality, demonstrating that the effects of GenAI are not merely about adoption but also about its intensity of use. Second, we define entrepreneurial judgment quality as an associational pathway between entrepreneurial uses of GenAI and business performance, and determine that this indirect association is systematic over the range of entrepreneurial uses of GenAI. Third, we show that this relationship is moderated by the founder's technical expertise, arguing that this is important because the founder must be able to navigate the relationship with AI.

## **2. Theoretical Background and Hypotheses**

### ***2.1. The AI Empowerment–Entrapment Perspective***

For a long time, technology and human cognition have been recognized as a double-edged sword. The potential for cognitive augmentation can also lead to dependency which means the ability to develop skills independently and critically be taken away (Risko & Gilbert, 2016). The power of GenAI is particularly significant in its role in activities that are traditionally human-intensive, such as ideation, writing, analysis, coding and strategic thinking. We do not claim that the empowerment–entrapment paradox is a theory in its own right, but rather a theoretical lens or conception that combines existing knowledge from cognitive offloading, entrepreneurial judgment, and epistemic risk studies related to AI usage. The empowerment dimension refers to GenAI's ability to boost entrepreneurial cognition, in ways of making more information available, offering more possibilities, speeding up experimentation, and lowering the routine demands of cognition. The entrapment dimension captures how entrenched it is to become to be so dependent on GenAI that they become less inclined to evaluate things independently, more inclined to trust in ideas that are not sufficiently backed up, and less likely to deal with the uncertainty involved in making entrepreneurial decisions.

This view is based on three theories. First, the cognitive offloading theory (Risko & Gilbert, 2016) implies that they rely on external sources to offload the internal cognitive load. Being efficient, too much



offloading can change or decrease engagement in internally operated cognitive processes. Secondly, entrepreneurial judgment theory (Knight, 1921; Foss & Klein, 2012) suggests that entrepreneurs must make decisions when information is incomplete and, as such, conditions of uncertainty exist. GenAI can assist in processing information but cannot eliminate the need for judgment. Third, recent research on plausibility regimes mediated by AI (Madjdi & Wurth, 2026) suggests that AI might change the epistemic circumstances in which entrepreneurial beliefs are developed, potentially leading to plausibility inflation, which is the tendency to consider coherent outputs generated by AI as accepted truths. Current views have largely addressed whether and how AI can enhance or impair cognition, but they have not sufficiently detailed how these opposing forces might change with heavier usage of AI. This empowerment–entrapment perspective helps fill this gap by viewing the intensity of AI use as the state in which the marginal value of AI use first rises but then begins to fall because of the associated costs of dependence.

## **2.2. GenAI Use Intensity and Entrepreneurial Judgment (H1)**

Entrepreneurial judgment refers to the capacity to make decisions under uncertainty, evaluating incomplete information, identifying viable opportunities, and adapting to changing conditions (Foss & Klein, 2012). We operationalize entrepreneurial judgment quality as founders' perceived quality of entrepreneurial judgment their perceived capability to evaluate opportunities, integrate incomplete information, and make resource-allocation and strategic decisions under uncertainty. GenAI may be linked to the quality of judgments through several mechanisms. GenAI's ability to quickly generate diverse alternatives can expand the search space of entrepreneurial options (Shepherd & Majchrzak, 2022). It can reduce the cognitive load of processing routine information, enabling founders to focus their attention on higher-order evaluation and strategic reasoning. It can be a "creative provocateur," challenging assumptions and exposing founders to perspectives they wouldn't otherwise encounter. But founders may be outsourcing important judgment tasks to systems that generate outputs through probabilistic recombination of historical data if they become too reliant on GenAI. Such outputs may appear coherent, even if they lack situated grounding (Madjdi & Wurth, 2026). Entrepreneurs could mistake plausibility for validity, leading to overconfidence and less independent assessment. Repeated offloading may change cognitive processing demands and decrease engagement with independent evaluation (Risko & Gilbert, 2016). Therefore, the marginal benefit of using GenAI is likely to increase first and then decline, leading to a concave relationship. Whether the observed usage is large enough to result in a full inverted-U shape is an empirical question, depending on whether usage becomes high enough that costs outweigh benefits. Hence, we propose:

**Hypothesis 1 (H1):** GenAI use intensity is positively associated with entrepreneurial judgment quality but with diminishing marginal effects such that the marginal association between GenAI use intensity and entrepreneurial judgment quality diminishes as use intensity increases.

## **2.3. Entrepreneurial Judgment Quality and Venture Performance (H2)**

Entrepreneurial decisions decide which opportunities are pursued, which resources are allocated, and which strategies are followed. Higher quality judgment should be linked to better venture performance through the reduction of costly decision errors, the improvement of resource allocation and the enabling of more effective adaptation to changing market conditions (Foss & Klein, 2012; Covin & Slevin, 1989). In the genAI context, the value of AI-generated information hinges critically on the founders' ability to evaluate and contextualize. Founders who use GenAI as a tool to augment their own high-quality judgment rather than a replacement for their own judgment should be better positioned to convert AI-generated insights into venture success. We therefore propose

**Hypothesis 2 (H2):** Entrepreneurial judgment quality is positively associated with new venture performance.

## **2.4. Entrepreneurial Judgment as an Associational Pathway (H3)**

The above arguments imply that GenAI use intensity might be associated with venture performance through the quality of entrepreneurial judgment. However, this indirect association should vary across the range of GenAI use, because the first-stage relationship is non-linear. For lower levels of use, more GenAI use may be associated with better judgment, which in turn may have a positive indirect relationship with



performance. As the use increases, the marginal indirect association should decline and might be negative at sufficiently high levels for some founders. This pattern can be especially pronounced when founders do not possess the capabilities to critically evaluate the outputs of AI. We therefore propose

**Hypothesis 3 (H3):** The conditional instantaneous indirect association between GenAI use intensity and venture performance through entrepreneurial judgment quality decreases as GenAI use intensity increases.

Because the first-stage association is non-linear, the indirect association is evaluated locally at different levels of GenAI use, rather than being captured by a single constant indirect effect. Since the entrepreneurial judgment and venture performance were measured at the same time (Time 2), H3 is considered as indirect association after mediation, not causal mediation.

### ***2.5. Founder Technical Expertise as a Boundary Condition (H4)***

Not all founders are equally prepared to cope with the empowerment–entrapment trade-off. Founders with technical expertise will be able to identify technically implausible outputs, understand system limits, critically assess AI recommendations and combine AI outputs with domain knowledge (Cao & Bhatia, 2025; Rady, Townsend & Hunt, 2026). Thus, founders with stronger technical backgrounds may be less vulnerable to the entrapment effects of excessive GenAI use. They have the knowledge to challenge AI outputs and maintain independent evaluation. This means they can use GenAI more heavily without the same loss in judgment quality. Those with no technical background, in contrast, may be more susceptible to plausibility inflation, with the quality of the judgment deteriorating more rapidly at high levels of usage. Hence, we predict the founder's technical expertise to neutralize the negative curvature of the GenAI–judgment relationship.

**Hypothesis 4 (H4):** Founder technical expertise weakens the negative curvature in the association between GenAI use intensity and entrepreneurial judgment quality.

## **3. Methods**

### ***3.1. Research Design and Sample***

A two-wave survey design was used. The two-wave design allows for the assessment of GenAI use to be separated from the T2 assessments of judgment and performance, thus mitigating some concerns raised by using the single-wave design. Note, however, that since judgment and performance were assessed at the same time point at T2, it is not possible to establish temporal precedence between the mediator and the outcome. The target group consisted of technology-based venture founders who have been in business for 6 months to 5 years. The participants were identified via venture capital databases, accelerator networks, entrepreneurial associations and founder networks in North America and Europe. 1247 founders were approached. A total of 412 responded to the initial survey (33.0% response rate) at Time 1. The adoption of GenAI was measured at T1. About four months later, the participants who finished the Time 1 survey were asked to fill out a follow-up survey. Of the 412 Time 1 respondents, 287 completed the Time 2 survey (69.7% retention). Of these 287, 75 did not report using GenAI, leaving a final analytical sample of 212 GenAI-adopting founders. The final analytical sample included 212 GenAI-adopting founders (51.5% of the Time 1 sample and 17.0% of the sample of all founders originally contacted). The research question was narrowed down to the technology venture founders who are using the GenAI technology, and those who are not, were not included in the study as the focus of the study is on the intensity of the usage of the GenAI technology, rather than on adoption or not.

Founders were identified as such by professional information from LinkedIn profiles or company websites. Unique survey links were used to avoid duplicate responses. The final sample was 68.3% male, mean age 34.7 years (SD = 8.2), mean venture age 2.8 years (SD = 1.4). Among the various ventures, those in software (42.5%), fintech (18.8%), health technology (12.9%) and other technology-related sectors (25.8%) were all represented.

### ***3.2. Attrition Analysis***

Attrition was calculated as the percentage of Time 1 completers (N = 412) who did not complete the Time 2 survey (N = 287 completed; N = 125 attrited). The comparison for the attrition analysis was done on a separate basis for GenAI adoption, and on a separate basis for GenAI use intensity among GenAI adopters.



The attrition analysis is provided in table 1. No evidence was identified of any difference between adopters in terms of founder age, gender, or founder's familiarity with GenAI or technical expertise. This helps to minimize concerns with systematic attrition, but not completely eliminate unobserved selection effects.

**Table 1***Comparison of Time 2 Completers vs. Attritors*

| Variable                             | T2 Completers | Attritors    | Test Statistic  | p-value |
|--------------------------------------|---------------|--------------|-----------------|---------|
| Founder Age                          | 34.2 (8.1)    | 33.8 (8.5)   | $t = 0.84$      | 0.40    |
| Founder Gender (% male)              | 67.2%         | 69.8%        | $\chi^2 = 0.12$ | 0.73    |
| GenAI Adoption Status (% adopters)   | 73.9%         | 71.2%        | $\chi^2 = 0.34$ | 0.56    |
| GenAI Use Intensity (among adopters) | 4.08 (1.54)   | 4.15 (1.58)  | $t = 0.56$      | 0.58    |
| Technical Expertise (among adopters) | 0.04 (0.83)   | -0.03 (0.87) | $t = 0.93$      | 0.35    |

### 3.3. Measures

**GenAI Use Intensity.** Measured at Time 1 using five activity-specific items assessing frequency of GenAI use for: (a) ideation/opportunity recognition, (b) market research/customer analysis, (c) product development/prototyping, (d) marketing/content creation, and (e) strategic planning/decision-making. Responses ranged from 1 = "less than monthly" to 7 = "multiple times daily." Because the indicators represent distinct entrepreneurial activities rather than interchangeable manifestations of a common latent trait, the measure was modeled as a behavioral index rather than a reflective scale. GenAI use intensity was calculated as the equal-weighted mean frequency of GenAI use across five entrepreneurial activities. Internal consistency (Cronbach's  $\alpha = 0.89$ ) is reported for descriptive purposes but should not be interpreted as evidence of reflective measurement. The primary analysis was restricted to GenAI adopters (use  $\geq 1$ ). For adopters, a score of 1 indicates less than monthly usage.

**Entrepreneurial Judgment Quality.** Measured at Time 2 using six items assessing: (a) evaluating venture feasibility, (b) identifying business model weaknesses, (c) distinguishing promising from unpromising opportunities, (d) making decisions under uncertainty, (e) adapting strategies to new information, and (f) integrating multiple information sources. Two AI-specific items ("recognize insufficiently grounded AI suggestions" and "maintain independent evaluation") were excluded a priori to avoid construct contamination. The six-item scale demonstrated acceptable reliability ( $\alpha = 0.84$ ; CR = 0.85; AVE = 0.51) and CFA fit ( $\chi^2 = 72.4$ , df = 27, CFI = 0.95, TLI = 0.93, RMSEA = 0.06, SRMR = 0.05; loadings = 0.61–0.83). Items were developed through literature review, expert review (five subject-matter experts), and pilot testing (n = 45). The scale assesses perceived entrepreneurial judgment quality the founder's perceived capability to evaluate opportunities, integrate incomplete information, and make resource-allocation and strategic decisions under uncertainty.

**New Venture Performance.** Measured at Time 2 using six subjective indicators: sales growth, profitability, market share, customer acquisition, performance relative to competitors, and performance relative to goals. CFA for the performance measure showed acceptable fit ( $\chi^2 = 34.2$ , df = 15, CFI = 0.97, TLI = 0.95, RMSEA = 0.05, SRMR = 0.04;  $\alpha = 0.88$ ; CR = 0.89; AVE = 0.54). Objective performance data (revenue growth) were available for a subsample of 89 ventures and used as supplementary analysis.

**Founder Technical Expertise.** Operationalized as a standardized composite index with four indicators: (a) formal technical education, (b) professional technical experience, (c) self-rated technical proficiency, and (d) ability to understand the venture's technical architecture and limitations. Technical expertise was defined as a multidimensional capability index, consisting of formal preparation, technical-system understanding, and accumulated technical experience, and perceived proficiency. The composite is meant to reflect breadth of technical ability of the founder and is not a reflection of a latent trait, so the indicators were summated after being standardized. Since the indicators had a different conceptual meaning, they were standardized and then summed together (Technical Expertise =  $[Z_1 + Z_2 + Z_3 + Z_4]/4$ ). VIFs were between 1.8 and 2.3; the composite was mean-centered prior to the building of interactions.



**Control Variables.** Controlled for founder age, gender (1 = male, 0 = female), education (1 = high school to 5 = doctoral), prior ventures, venture age, venture size (in terms of employees) and industry (software, fintech, health technology reference, other technology reference), as well as technological optimism ( $\alpha = 0.82$ ).

### 3.4. Analytical Strategy

The hierarchical polynomial regression with HC3 heteroskedasticity-consistent standard errors was used. Before adding the quadratic and interaction terms to eliminate unnecessary multicollinearity (Aiken & West, 1991), the use intensity of GenAI was mean-centered ( $M = 4.12$ ). The term which was centered and squared was then computed as ( $X\_c^2$ ). The baseline model was:  $JQ = \beta_0 + \beta_1 X\_c + \beta_2 X\_c^2 + \Sigma \beta_k \text{Controls} + \varepsilon$ . The moderated polynomial model was:  $JQ = \beta_0 + \beta_1 X\_c + \beta_2 X\_c^2 + \beta_3 W + \beta_4 X\_c W + \beta_5 X\_c^2 W + \Sigma \beta_k \text{Controls} + \varepsilon$ . Since H1 forecasts decreasing, rather than negative, marginal effects in the range of the data, the sign and significance of the quadratic term and the negative derivative are the most important tests. The Lind–Mehlum procedure is reported additionally to determine whether the concavity constitutes a full inverted-U. Concavity testing followed Lind and Mehlum (2010), requiring: (1) negative quadratic coefficient, (2) significant positive slope at the lower bound, (3) significant negative slope at the upper bound, and (4) turning point within the observed range (1–7). The derivative was calculated as  $dJQ/dX = \beta_1 + 2\beta_2 X\_c$ . Turning point transformations used  $X\_c^* = -\beta_1/(2\beta_2)$  and  $X^* = X\_c^* + \text{mean}(X)$ . Conditional quadratic coefficients were computed as  $\beta_2|W = \beta_2 + \beta_5 W$ . Conditional instantaneous indirect associations followed Hayes and Preacher (2010):  $IE(X, W) = [\beta_1 + 2\beta_2 X\_c + \beta_4 W + 2\beta_5 X\_c W] \times b$ . Power analysis using G\*Power 3.1 indicated that  $N = 212$  provides adequate power ( $\geq 0.80$ ) to detect moderate effect sizes ( $f^2 = 0.08$ ) with 15 predictors at  $\alpha = 0.05$ . However, the sample is underpowered to reliably detect small nonlinear and interaction effects ( $f^2 = 0.04$  requires  $N \approx 378$ ), and both the quadratic term ( $\Delta R^2 = 0.03$ ) and the interaction ( $\Delta R^2 = 0.03$ ) fall in this smaller effect-size range. Readers should weight the corresponding hypothesis tests accordingly; we return to this point when interpreting these specific results in Sections 4.3–4.4 and 5.1.

### 3.5. Common-Method Bias Assessment

To assess common-method bias, we conducted Harman's single-factor test. The unrotated factor solution extracted six factors with eigenvalues  $> 1.0$ , and the first factor accounted for 28.4% of the total variance, well below the 50% threshold. This result provides no indication from this diagnostic that a single general factor accounts for most observed variance; however, Harman's test is limited as a diagnostic of common-method variance. A combined two-factor CFA model distinguishing JQ (six items) and performance (six items) was estimated. The two-factor model ( $\chi^2 = 184.6$ ,  $df = 53$ ,  $CFI = 0.93$ ,  $TLI = 0.91$ ,  $RMSEA = 0.07$ ,  $SRMR = 0.06$ ) fit substantially better than the one-factor model combining all twelve items ( $\chi^2 = 412.6$ ,  $df = 54$ ,  $CFI = 0.68$ ,  $RMSEA = 0.15$ ;  $\Delta\chi^2(1) = 228.0$ ,  $p < 0.001$ ), providing evidence that the two constructs are empirically distinguishable and reducing, but not eliminating, concern that a single common method factor accounts for their covariance. However, because JQ and performance were measured concurrently at T2, the judgment–performance association may still be partially influenced by same-source bias.

## 4. Results

### 4.1. Descriptive Statistics

Table 2 presents descriptive statistics and correlations. GenAI use intensity ( $M = 4.12$ ,  $SD = 1.56$ ), entrepreneurial judgment quality ( $M = 5.18$ ,  $SD = 1.12$ ), and venture performance ( $M = 4.76$ ,  $SD = 1.24$ ) were all above scale midpoints. GenAI use correlated positively with judgment ( $r = 0.18$ ,  $p < 0.01$ ) and performance ( $r = 0.14$ ,  $p < 0.05$ ). Judgment correlated with performance ( $r = 0.32$ ,  $p < 0.01$ ), consistent with H2. The modest usage–judgment correlation is compatible with a nonlinear relationship. GenAI use distribution: minimum = 1,  $P25 = 3$ , median = 4,  $P75 = 5$ , maximum = 7.

**Table 2**

*Descriptive Statistics and Correlations*

| Variable               | M    | SD   | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|------------------------|------|------|---|---|---|---|---|---|---|---|---|----|----|
| 1. GenAI Use Intensity | 4.12 | 1.56 | — |   |   |   |   |   |   |   |   |    |    |



| Variable                            | M     | SD   | 1     | 2     | 3    | 4     | 5     | 6   | 7   | 8    | 9    | 10  | 11 |
|-------------------------------------|-------|------|-------|-------|------|-------|-------|-----|-----|------|------|-----|----|
| 2. Entrepreneurial Judgment Quality | 5.18  | 1.12 | .18** | —     |      |       |       |     |     |      |      |     |    |
| 3. Venture Performance              | 4.76  | 1.24 | .14*  | .32** | —    |       |       |     |     |      |      |     |    |
| 4. Founder Technical Expertise      | 0.00  | 0.85 | .11   | .19** | .16* | —     |       |     |     |      |      |     |    |
| 5. Founder Age                      | 34.70 | 8.20 | -.06  | .04   | .09  | .07   | —     |     |     |      |      |     |    |
| 6. Founder Gender                   | 0.68  | 0.47 | .02   | .01   | -.02 | .11   | .04   | —   |     |      |      |     |    |
| 7. Education                        | 3.82  | 1.04 | .04   | .08   | .05  | .28** | .06   | .02 | —   |      |      |     |    |
| 8. Prior Ventures                   | 2.10  | 1.70 | -.04  | .11   | .13* | .08   | .22** | .03 | .01 | —    |      |     |    |
| 9. Venture Age                      | 2.80  | 1.40 | .08   | .06   | .10  | .04   | .18** | .02 | .05 | .14* | —    |     |    |
| 10. Venture Size (ln)               | 2.14  | 1.08 | .07   | .05   | .11  | .03   | .12   | .01 | .04 | .09  | .13* | —   |    |
| 11. Technological Optimism          | 4.52  | 1.18 | .15*  | .12*  | .14* | .09   | .04   | .01 | .06 | .03  | .05  | .02 | —  |

\*Note: n = 212. Gender: 1 = male, 0 = female. Education: 1 = high school to 5 = doctoral. Technical expertise was standardized/mean-centered. Venture size is natural log of number of employees. Pearson correlations reported; point-biserial correlations used for gender. Discriminant validity statistics (HTMT) are reported in the Measurement Assessment section. \*p < 0.05; \*\*p < 0.01.

#### 4.2. Measurement Assessment

The entrepreneurial judgment CFA showed acceptable fit ( $\chi^2 = 72.4$ , df = 27, CFI = 0.95, TLI = 0.93, RMSEA = 0.06, SRMR = 0.05). Loadings ranged 0.61–0.83; CR = 0.85; AVE = 0.51. Performance demonstrated CR = 0.89; AVE = 0.54. Discriminant validity was supported (AVE square roots exceeded inter-construct correlations; HTMT < 0.85 for all pairs).

#### 4.3. Nonlinear Association Between GenAI Use and Entrepreneurial Judgment

Table 3 presents hierarchical regression results. Model 3 reveals a significant positive linear coefficient for centered X ( $b = 0.82$ , SE = 0.32,  $p < 0.01$ ) and negative quadratic coefficient ( $b = -0.09$ , SE = 0.04,  $p < 0.05$ ). The quadratic model significantly improved fit over the linear model ( $\Delta R^2 = 0.03$ ), and a robust Wald test indicated that the quadratic coefficient significantly improved model specification (Wald  $\chi^2(1) = 5.06$ ,  $p < 0.05$ ), supporting the nonlinear specification.

The turning point on the centered scale is:  $X_{c*} = -b_1/(2b_2) = -0.82/(2 \times -0.09) = 4.56$ . Using  $X^* = X_{c*} + 4.12$ , the original-scale turning point is  $X^* = 4.56 + 4.12 = 8.68$  (95% CI: 7.12–10.24). This value lies outside the observed 1–7 scale. The derivative is  $dJQ/dX = b_1 + 2b_2X_{c*}$ . At  $X = 1$  ( $X_{c*} = -3.12$ ): slope =  $0.82 + 2(-0.09)(-3.12) = 0.82 + 0.5616 = 1.3816$  (SE = 0.42,  $p < 0.01$ ). At  $X = 7$  ( $X_{c*} = 2.88$ ): slope =  $0.82 + 2(-0.09)(2.88) = 0.82 - 0.5184 = 0.3016$  (SE = 0.16,  $p = 0.06$ ). The estimated slope remains positive at both endpoints, although the upper-bound slope is not statistically distinguishable from zero.

The Lind–Mehlum test shows that the negative quadratic coefficient is significant (condition 1 satisfied). The lower-bound slope is positive and significant (condition 2 satisfied). The upper-bound slope is not significantly negative (condition 3 not satisfied). The turning point (8.68) lies outside the observed range (condition 4 not satisfied). Therefore, the reported coefficients do not establish an inverted-U within the 1–7 observed range. The quadratic coefficient is negative, indicating concavity and diminishing marginal returns, but the estimated extremum lies outside the observed 1–7 usage range. The reported coefficients therefore provide evidence of a concave relationship with estimated positive slopes throughout the observed range, rather than a full inverted-U.

H1 was supported with respect to diminishing marginal returns. The quadratic coefficient was negative and statistically significant ( $b = -0.09$ , SE = 0.04,  $p < 0.05$ ), and the estimated marginal association declined



as GenAI use increased. However, the estimated turning point of 8.68 was outside the observed 1–7 range, and the upper-bound slope was not statistically distinguishable from zero ( $b = 0.30$ ,  $p = 0.06$ ). Thus, the data support a concave diminishing-return pattern rather than a full inverted-U within the observed range. As discussed in Section 3.4, this effect size ( $\Delta R^2 = 0.03$ ) falls below the threshold at which the study is adequately powered, so the quadratic coefficient, while significant at  $p < 0.05$ , should be treated as a preliminary rather than a well-powered estimate of curvature.

**Table 3**

*Polynomial Regression Predicting Entrepreneurial Judgment Quality*

| Variable                           | Model 1      | Model 2      | Model 3       | Model 4       | Model 5       |
|------------------------------------|--------------|--------------|---------------|---------------|---------------|
|                                    | b (SE)       | b (SE)       | b (SE)        | b (SE)        | b (SE)        |
| <b>Controls</b>                    |              |              |               |               |               |
| Founder Age                        | 0.01 (0.01)  | 0.01 (0.01)  | 0.01 (0.01)   | 0.01 (0.01)   | 0.01 (0.01)   |
| Founder Gender                     | 0.04 (0.12)  | 0.04 (0.12)  | 0.05 (0.12)   | 0.04 (0.12)   | 0.04 (0.12)   |
| Education                          | 0.08 (0.07)  | 0.07 (0.07)  | 0.07 (0.07)   | 0.06 (0.07)   | 0.06 (0.07)   |
| Prior Ventures                     | 0.06 (0.04)  | 0.05 (0.04)  | 0.05 (0.04)   | 0.04 (0.04)   | 0.04 (0.04)   |
| Venture Age                        | 0.03 (0.05)  | 0.03 (0.05)  | 0.03 (0.05)   | 0.02 (0.05)   | 0.02 (0.05)   |
| Venture Size (ln)                  | 0.04 (0.03)  | 0.03 (0.03)  | 0.03 (0.03)   | 0.03 (0.03)   | 0.03 (0.03)   |
| Technological Optimism             | 0.12* (0.05) | 0.10 (0.05)  | 0.09 (0.05)   | 0.09 (0.05)   | 0.08 (0.05)   |
| <b>Main Effects</b>                |              |              |               |               |               |
| GenAI Use ( $X_c$ )                |              | 0.12* (0.05) | 0.82** (0.32) | 0.80** (0.32) | 0.78** (0.32) |
| GenAI Use <sup>2</sup> ( $X_c^2$ ) |              |              | -0.09* (0.04) | -0.09* (0.04) | -0.08* (0.04) |
| Technical Expertise (W)            |              |              |               | 0.16** (0.06) | 0.15** (0.06) |
| <b>Interactions</b>                |              |              |               |               |               |
| $X_c \times W$                     |              |              |               | 0.04 (0.04)   | 0.04 (0.04)   |
| $X_c^2 \times W$                   |              |              |               |               | 0.09* (0.04)  |
| R <sup>2</sup>                     | 0.08         | 0.11         | 0.14          | 0.17          | 0.20          |
| Adjusted R <sup>2</sup>            | 0.05         | 0.07         | 0.09          | 0.11          | 0.13          |
| $\Delta R^2$                       |              | 0.03         | 0.03*         | 0.03*         | 0.03*         |
| Wald $\Delta\chi^2$                |              | 2.34         | 5.06*         | 7.12*         | 9.68*         |
| Model Wald $\chi^2$                | 15.8         | 21.4*        | 30.5**        | 40.3***       | 48.9***       |

\*Note:  $n = 212$ . HC3 robust SEs.  $X_c$  = mean-centered GenAI use ( $M = 4.12$ ). Model 1: controls only. Model 2: controls + X. Model 3: controls + X + X<sup>2</sup> (tests H1). Model 4: controls + X + X<sup>2</sup> + W + XW. Model 5: controls + X + X<sup>2</sup> + W + XW + X<sup>2</sup>W (tests H4). Industry dummies (software, fintech, health technology) included but not displayed; other technology ventures served as reference category. Turning points transformed back to original 1–7 scale: baseline turning point = 8.68 (95% CI: 7.12–10.24), outside observed range. Endpoint slopes at  $X=1$ : 1.38 ( $p < 0.01$ ); at  $X=7$ : 0.30 ( $p = 0.06$ ). Wald  $\Delta\chi^2$  tests use robust covariance. \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

#### 4.4. Moderating Role of Technical Expertise

Table 3 Model 5 shows the  $X_c^2 \times W$  interaction was positive ( $b = 0.09$ ,  $SE = 0.04$ ,  $p < 0.05$ ), supporting curvature attenuation. Conditional quadratic coefficients (using the full variance-covariance matrix formula  $\text{Var}(b_2 + b_5W) = \text{Var}(b_2) + W^2\text{Var}(b_5) + 2W \text{Cov}(b_2, b_5)$ ): At low expertise ( $W = -0.85$ ):  $b_2|W = -0.08 + 0.09(-0.85) = -0.1565$  ( $SE = 0.062$ ,  $p < 0.05$ ). At mean expertise ( $W = 0$ ):  $b_2|W = -0.08$  ( $SE = 0.040$ ,  $p < 0.05$ ). At high expertise ( $W = +0.85$ ):  $b_2|W = -0.08 + 0.09(0.85) = -0.0035$  ( $SE = 0.048$ ,  $p = 0.94$ ). Thus, the curvature is significantly negative at low and mean expertise and approaches zero at high expertise (not significantly different from zero).

Conditional turning points (using  $X|W = -(b_1 + b_4W) / [2(b_2 + b_5W)] + 4.12$ ; 95% bootstrap CI): At low expertise ( $W = -0.85$ ):  $X_c = -(0.78 + 0.04[-0.85]) / (2[-0.1565]) = 2.38$ ;  $X^* = 2.38 + 4.12 = 6.50$  (95% CI: 5.21–7.79). At mean expertise ( $W = 0$ ):  $X_c^* = -0.78 / (2[-0.08]) = 4.875$ ;  $X^* = 4.875 + 4.12 = 8.995$  (95%



CI: 7.02–10.97). At high expertise ( $W = +0.85$ ): At high expertise, the quadratic component was not statistically distinguishable from zero ( $b_2|W = -0.0035$ ,  $p = 0.94$ ), so a substantively meaningful turning point could not be established.

Conditional endpoint slopes at  $X=7$ : At low expertise ( $W = -0.85$ ): slope =  $(0.78 + 0.04[-0.85]) + 2(-0.1565)(2.88) = 0.746 - 0.901 = -0.155$  ( $p = 0.08$ ). At mean expertise ( $W = 0$ ): slope =  $0.78 + 2(-0.08)(2.88) = 0.78 - 0.461 = 0.319$  ( $p = 0.06$ ). At high expertise ( $W = +0.85$ ): slope =  $(0.78 + 0.04[0.85]) + 2(-0.0035)(2.88) = 0.814 - 0.020 = 0.794$  ( $p < 0.01$ ). In cases of low technical expertise the estimated curvature was significantly more negative and the estimated extremum was within the range of observation ( $X^* = 6.50$ ). There was, however, only a slight negative upper-bound slope ( $p = 0.08$ ); thus, the evidence points to more diminishing returns at low expertise, but didn't say so. The turning point is at 8.995 which is outside the measured range at the expert level. At high expertise no turning point can be discerned within the range of observations to warrant any empirical meaning. The relationship approaches linearity as expertise increases. The positive interaction between  $X_c \times W$  was in line with the H4 hypothesis, suggesting that the negative quadratic effect was reduced with higher technical skills. This interaction effect size ( $\Delta R^2 = 0.03$ ), as discussed in Section 3.4, is smaller than the study was powered to reliably detect and could be interpreted as suggesting a direction of moderation consistent with H4, but requires further replication in a larger sample before it can be understood as a settled result.

#### **4.5. Entrepreneurial Judgment Quality and Venture Performance**

The quality of judgment was positively correlated with performance ( $b = 0.29$ ,  $SE = 0.06$ ,  $p < 0.001$ ) when adjusted for GenAI use and covariates (see Table 4). H2 is supported as an association. In the case of the T2 co-measurement of judgment and performance, causal interpretation is not possible. The result regression indicates the relationship between entrepreneurial judgment quality and venture performance, accounting for the portion of variance shared by them.

**Table 4**

*Regression Predicting Venture Performance*

| <b>Variable</b>                    | <b>Model 1</b> | <b>Model 2</b> | <b>Model 3</b> |
|------------------------------------|----------------|----------------|----------------|
|                                    | <b>b (SE)</b>  | <b>b (SE)</b>  | <b>b (SE)</b>  |
| <b>Controls</b>                    |                |                |                |
| Founder Age                        | 0.01 (0.01)    | 0.01 (0.01)    | 0.01 (0.01)    |
| Founder Gender                     | 0.06 (0.13)    | 0.04 (0.13)    | 0.04 (0.12)    |
| Education                          | 0.06 (0.08)    | 0.05 (0.08)    | 0.03 (0.07)    |
| Prior Ventures                     | 0.07 (0.04)    | 0.06 (0.04)    | 0.05 (0.04)    |
| Venture Age                        | 0.05 (0.05)    | 0.04 (0.05)    | 0.03 (0.05)    |
| Venture Size (ln)                  | 0.08 (0.03)    | 0.06 (0.03)    | 0.05 (0.03)    |
| Technological Optimism             | 0.13* (0.05)   | 0.11 (0.05)    | 0.09 (0.05)    |
| <b>Main Effects</b>                |                |                |                |
| GenAI Use ( $X_c$ )                |                | 0.07 (0.05)    | 0.04 (0.05)    |
| GenAI Use <sup>2</sup> ( $X_c^2$ ) |                | -0.02 (0.02)   | -0.01 (0.02)   |
| Entrepreneurial Judgment Quality   |                |                | 0.29*** (0.06) |
| $R^2$                              | 0.09           | 0.13           | 0.21           |
| Adjusted $R^2$                     | 0.06           | 0.09           | 0.17           |
| $\Delta R^2$                       |                | 0.04*          | 0.08***        |
| Model Wald $\chi^2$                | 18.2           | 30.4**         | 52.7***        |

\*Note:  $n = 212$ . HC3 robust SEs.  $X_c$  = mean-centered GenAI use. Industry dummies included but not displayed. \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

#### **4.6. Conditional Instantaneous Indirect Associations**

Because entrepreneurial judgment quality and venture performance were both measured at Time 2, the following analysis characterizes a conditional associational decomposition rather than a test of causal mediation; we retain the term "indirect association" for consistency with the polynomial moderated-mediation



framework (Hayes & Preacher, 2010), but temporal precedence between judgment quality and performance cannot be established with the present design. Using Model 5 mediator coefficients and Table 4 Model 3 outcome coefficients, the conditional instantaneous indirect association is:  $IE(X, W) = [0.78 + 2(-0.08)X_c + 0.04W + 2(0.09)X_cW] \times 0.29 = [0.78 - 0.16X_c + 0.04W + 0.18X_cW] \times 0.29$ .

**Table 5: Conditional Instantaneous Indirect Associations at Representative Values**

| GenAI Use (X) | X <sub>c</sub> | Expertise | Conditional Instantaneous IE | 95% BC Bootstrap CI | Inference       |
|---------------|----------------|-----------|------------------------------|---------------------|-----------------|
| 1             | -3.12          | Low       | 0.500                        | [0.214, 0.786]      | Significant     |
| 1             | -3.12          | Mean      | 0.371                        | [0.142, 0.589]      | Significant     |
| 1             | -3.12          | High      | 0.242                        | [0.098, 0.438]      | Significant     |
| 3             | -1.12          | Low       | 0.318                        | [0.114, 0.521]      | Significant     |
| 3             | -1.12          | Mean      | 0.278                        | [0.103, 0.467]      | Significant     |
| 3             | -1.12          | High      | 0.238                        | [0.089, 0.429]      | Significant     |
| 5             | 0.88           | Low       | 0.136                        | [-0.023, 0.312]     | Marginal        |
| 5             | 0.88           | Mean      | 0.185                        | [0.032, 0.367]      | Significant     |
| 5             | 0.88           | High      | 0.234                        | [0.081, 0.412]      | Significant     |
| 7             | 2.88           | Low       | -0.045                       | [-0.218, 0.134]     | Not significant |
| 7             | 2.88           | Mean      | 0.093                        | [-0.019, 0.243]     | Marginal        |
| 7             | 2.88           | High      | 0.230                        | [0.072, 0.409]      | Significant     |

*Note: Bootstrap based on 5,000 resamples with bias-corrected confidence intervals. Low expertise =  $W = -0.85$  (one SD below mean); Mean expertise =  $W = 0$ ; High expertise =  $W = +0.85$  (one SD above mean).*

The derivative of the conditional instantaneous indirect association with respect to X is:  $\partial IE / \partial X = 2(b_2 + b_3W)b$ . At  $W = 0$ :  $2(-0.08)(0.29) = -0.0464$  (SE = 0.021,  $p < 0.05$ ). At  $W = +0.85$ :  $2(-0.0035)(0.29) = -0.0020$  (SE = 0.028,  $p = 0.94$ ). At  $W = -0.85$ :  $2(-0.1565)(0.29) = -0.0908$  (SE = 0.036,  $p < 0.01$ ). At mean expertise, the conditional instantaneous indirect association decreases by approximately 0.046 per one-unit increase in GenAI use; at high expertise the decline is not statistically distinguishable from zero ( $p = 0.94$ ); at low expertise the decline is steeper and statistically significant ( $p < 0.01$ ). These patterns suggest that higher technical expertise is associated with a reduced rate of decline in the indirect association, though as noted above, these estimates reflect concurrent measurement of judgment and performance and should be read as associational rather than mediational evidence.

The evidence for H3 was conditional: the derivative of the conditional instantaneous indirect association was negative and significant at low and mean expertise but not at high expertise. Conditional instantaneous indirect associations are positive at lower usage and diminish as usage increases. However, at mean and high expertise, the indirect association does not become negative within the observed range. At low expertise, it becomes marginally negative only at the highest usage level. This suggests diminishing indirect benefits rather than a full reversal.

#### **4.7. Robustness Analyses**

Adoption-inclusive sensitivity analysis ( $n = 287$ ) showed that the 0–7 specification combining adoption and intensity produces a different construct; results are not directly comparable. Quadratic coefficient for the full sample:  $b = -0.04$  (SE = 0.03,  $p = 0.18$ ), suggesting that the nonlinearity is specific to the adopter subsample. The quadratic coefficient for objective performance ( $n = 89$ ) was similar in direction ( $b = -0.07$ , SE = 0.04,  $p < 0.10$ ), though the evidence was weak. This full-sample pattern is consistent with the quadratic effect confirmed in the primary adopter-only model (Wald  $\chi^2(1) = 5.06$ ,  $p < 0.05$ ; see Section 4.3). Given the small size of the samples, restricted cubic spline analysis (3 knots) was also directionally consistent with quadratic specification, with a decrease in returns. All VIFs < 2.5; Polynomial models create correlation between X and X<sup>2</sup> by design, so it's important to focus on the response function rather than individual parameters. There were no observations that exceeded  $4/n = 0.0189$ , with a maximum Cook's D of 0.012. There was a consistent quadratic coefficient ( $b = -0.08$ , SE = 0.04,  $p < 0.05$ ) when AI-specific items (six-item primary measure) were excluded. Breusch-Pagan:  $\chi^2 = 4.12$ ,  $p = 0.25$ , indicating no significant



heteroskedasticity; HC3 robust standard errors were nonetheless retained as a conservative default. The Shapiro-Wilk test for normality was not statistically significant ( $W = 0.98$ ,  $p = 0.12$ ) and the Q-Q plot showed reasonable normality. Removing data at the upper tail ( $X > 6$ ,  $n = 23$ ) gave similar but slightly less marked quadratic coefficient ( $b = -0.07$ ,  $SE = 0.04$ ,  $p < 0.10$ ) suggesting that the concavity is not just due to the extreme observations.

## **5. Discussion**

### **5.1. Theoretical Contributions**

This study contributes to the knowledge of GenAI in entrepreneurship in three ways. First, we investigate the intensity of the use of GenAI and find evidence that this is negatively associated with the perceived entrepreneurial judgment quality. The negative quadratic coefficient ( $b = -0.09$ ,  $p < 0.05$ ) suggests that the marginal returns to the application of GenAI are decreasing. Importantly, the estimated turning point is outside the range of observations ( $X^* = 8.68$ ) making the empirical pattern more indicative of diminishing marginal returns than an observed inverted-U. This resolves the conflicting results from the literature which showed positive impact (Duong et al., 2026; Cao & Bhatia, 2025) and negative impact (Impink & Wright, 2025; Dell'Acqua et al., 2023) by proposing that the relationship would depend on their usage of GenAI, and that any complete negative impact would only manifest beyond the usage level found in our sample. Although not measured directly, the concave pattern fits the theoretical framework of "passive" augmenting effects giving way to more "active" dependence-related costs as use increases. With moderate use, the benefits of augmentation can outweigh: GenAI facilitates information search, provides options, and eases cognitive strain. With high usage, entrapment costs can outweigh benefits: cognitive offloading can lead to less independent evaluation, plausibility inflation can make people more confident in ideas which are less well-founded, and people can become more dependent on AI output. However, in our sample, these costs do not fully offset benefits within the observed range. This interpretation aligns with Madjdi and Wurth's (2026) argument that AI alters the epistemic conditions of entrepreneurial judgment and Rady, Townsend, and Hunt's (2026) emphasis on distinguishing useful from hallucinated AI outputs.

Second, we identify entrepreneurial judgment quality as an associational pathway linking GenAI use intensity with venture performance. The conditional instantaneous indirect association patterns positive at lower usage, diminishing at higher usage suggest that GenAI's performance implications may operate through judgment quality. This extends prior work on direct GenAI-performance effects (Duong et al., 2026) by specifying the cognitive pathway through which GenAI may influence venture outcomes. Importantly, the derivative of the conditional instantaneous indirect association ( $\partial IE / \partial X = -0.046$  at mean expertise) provides formal evidence that the marginal indirect benefit declines with increasing use. Third, we demonstrate that higher technical expertise was associated with substantially weaker negative curvature, suggesting that technical expertise may buffer against diminishing returns from intensive GenAI use. At high expertise, the quadratic component approaches zero ( $b_2|W=+0.85 = -0.0035$ , ns), suggesting that the relationship becomes approximately linear. This is consistent with Cao and Bhatia's (2025) finding that founder expertise shapes GenAI outcomes and extends it by showing that expertise specifically buffers against the diminishing returns associated with intensive GenAI use. The curve is steeper at low expertise and the estimated extremum or maximum (6.50) is just within the range of observed usage levels, so that less technically skilled founders may suffer from severe diminishing returns at high use levels. The conditional endpoint slope for low level of expertise ( $X = 7$ ) is negative, but just outside of the bounds of significance ( $p = 0.08$ ), giving some indication that the relationship might reverse near the upper end of less expert founders. This moderation effect ( $\Delta R^2 = 0.03$ ) is not sufficiently large to be considered as a boundary condition for the present study (and is certainly not sufficiently large to warrant replication with a larger sample) and should be interpreted as a preliminary pattern rather than a true boundary condition.

### **5.2. Practical Implications**

The critical implication for entrepreneurs is that using GenAI is not enough - it is as important what you use it for. According to our findings, there is an increase in judgment quality with greater use of GenAI within its typical range of use, with diminishing returns the further out of its typical range of use. Safeguards



could involve the implementation of "AI-off" blocks of critical thinking time, delegation logs to track what tasks have been delegated to AI, and capability-floor checks to ensure independent proficiency (Dell'Acqua et al., 2023). Founders should be able to make a possibility judgement rather than plausibility judgements by questioning about the possibility of hallucination first, rather than making a plausibility judgement first and asking about the possibility of hallucination later (Rady, Townsend & Hunt, 2026). For entrepreneurs without tech knowledge, our findings indicate that they may be at risk from very high usage of diminishing returns. The estimated extremum at low expertise, which is around 6.50 (close to the top of the scale), suggests that there may be a decline in the quality of judgment when highly used. They might need to invest in technical literacy, find co-founders with technical skills or set up clear review cycles for AI-generated content. Given the results, investor due diligence efforts for investors might need to consider whether the ventures are using GenAI tools, and how the founders are using independent judgment alongside GenAI. The results emphasize the need for the development of AI literacy along with critical thinking for policymakers and educators. Instead of having access to technology, the difficulty to entrepreneurial success might be how to make sound judgments in using technology.

### **5.3. Limitations and Future Research**

There are a number of caveats to be noted. Self-reported use, judgment, and performance measurements of GenAI were used. Objective usage logs, API data and financial performance records should be included in future research. Our objective-performance subsample ( $n = 89$ ) serves as suggestive additional evidence, but is underpowered. Because the findings are based on technology ventures in North America and Europe, they may not extend to non-technology ventures or to other regions. There is a need for further studies to investigate the empowerment entrapment paradox in other types of entrepreneurial contexts. GenAI use was measured at Time 1, prior to judgment and performance, but judgment and performance were co-measured at Time 2, so temporal precedence between them cannot be established. Therefore, the question of causality cannot be answered. A three wave design (T1: use, T2: judgement, T3: performance) would give greater evidence. A scale of entrepreneurial judgment was created for this research. While preliminary reliability and validity evidence is acceptable, independent validation is needed. The concepts of cognitive offloading and dependence on AI were not directly assessed. The interpretation of entrapment is speculative and not empirically proven. The mechanisms of cognitive offloading, dependence on AI, and plausibility inflation were not measured directly and thus could not be directly tested as mediators between GenAI use intensity and entrepreneurial judgment quality. The mechanisms involved should be directly measured in future studies and it should be tested whether they mediate the nonlinear relationship. We concentrated on the technical expertise; other boundary conditions cognitive style, AI-literacy, entrepreneurial experience deserve investigation. The empowerment entrapment relationship can go through a changing process. Future studies will explore how to evaluate whether using GenAI over time can negatively affect independent decision-making skills. Since the turning point at the baseline (8.68) is not within the range of observation, care must be taken in any interpretation of this as the "peak". The data are more consistent with diminishing returns than a full inverted-U over the observed range of usage. The conditional turning point for low expertise (6.50) should be interpreted with caution given the marginal endpoint slope results. Limiting the intensity of GenAI use to a 1-7 frequency scale and not considering non-adopters limits the ability to see potential nonlinearities outside the observed range of observed usage. As discussed in Section 3.4, the sample size is underpowered to detect small effect sizes ( $f^2 = 0.04$ ). The quadratic and interaction effects ( $\Delta R^2 = 0.03$ ) are within this range. Therefore, while these effects are statistically significant at conventional levels, they should be considered preliminary findings that require replication in larger samples.

### **6. Conclusion**

Generative AI presents both opportunity and risk for entrepreneurship. This study provides evidence that GenAI use intensity is nonlinearly associated with perceived entrepreneurial judgment quality, exhibiting a concave relationship with diminishing marginal returns. Among GenAI-adopting founders, judgment quality increases with usage throughout the observed 1–7 range, but the marginal benefit declines as use intensifies. The estimated extremum (8.68 on the original scale) lies outside the observed range. The present data do not



establish whether dependence-related costs eventually produce a negative association, because the estimated overall extremum lies beyond the observed usage range. Entrepreneurial judgment quality is positively associated with venture performance. Founder technical expertise attenuates the negative curvature, indicating that technical capability moderates the relationship, with the curvature approaching zero at high expertise. The conditional instantaneous indirect association through judgment quality diminishes with increasing use, and this decline is most pronounced among less technically expert founders.

Because several of these findings particularly the curvature and moderation effects rest on small effect sizes below the study's adequately powered threshold, and because the mediation-consistent pathway linking GenAI use to performance rests on constructs measured concurrently rather than sequentially, these patterns should be treated as an initial account requiring replication with larger, longitudinally staged samples rather than a settled description of how GenAI use affects entrepreneurial judgment.

The broader implication is that GenAI's entrepreneurial value depends on the balance between cognitive augmentation and cognitive dependence. When used thoughtfully, GenAI may empower founders to recognize opportunities and make better decisions. When used uncritically, however, it may create conditions under which the marginal benefits of additional use diminish and, at sufficiently high levels, potentially reverse. The central implication is therefore that the entrepreneurial value of GenAI depends not merely on adoption, but on disciplined integration with human judgment.

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The author/s declare that there is no conflict of interest regarding the publication of this article.

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#### **Data Availability**

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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