

When Generative AI Builds or Undermines Entrepreneurial Capability

Violetta Bacon-Gerasymenko¹, Andrew C. Corbett², William J. Wales³

¹Oregon State University, College of Business, USA

²Arthur M. Blank Center for Entrepreneurship Office, Babson College, USA

³Massry School of Business, University at Albany, USA

violetta.gerasymenko@oregonstate.edu

acorbett@babson.edu

wwales@albany.edu

Abstract: Generative AI (GenAI) is rapidly becoming foundational cognitive infrastructure for entrepreneurship. Yet a critical question remains: why does GenAI enhance entrepreneurial capability for some while quietly eroding it for others? Responding to the ETP Special Issue's call to move beyond main-effect accounts, this study advances a human-GenAI cognitive engagement framework that explains when GenAI functions as a competence-development rather than a competence-erosion tool. Drawing on goal orientation theory and entrepreneurial cognition, we demonstrate that GenAI's effects depend on the joint configuration of entrepreneurs' initial competence and motivational orientation, revealing a paradoxical downside of GenAI-enabled efficiency largely overlooked in entrepreneurship research.

1. Introduction

The transformative potential of generative AI (GenAI) in entrepreneurship has sparked intense scholarly debate, with perspectives ranging from universal productivity enhancer to threat to human skill development (Chalmers et al., 2021; Obschonka & Audretsch, 2020; Shepherd & Majchrzak, 2022). Yet as Obschonka et al. (2024) observe, the field lacks theoretical frameworks explaining why some individuals flourish with GenAI while others experience developmental stagnation. Recent work suggests the very convenience of AI tools may undermine the cognitive development they purport to support (Larson et al., 2024). We address this gap by introducing the individual-GenAI cognitive engagement model, integrating goal orientation theory with entrepreneurial cognition to explain heterogeneous developmental outcomes among nascent entrepreneurs (VandeWalle, 1997). Central to our approach is that GenAI's developmental impact cannot be understood through simple main effects (Otis et al., 2024). Meaningful insight emerges only when considering the triple interaction of initial competence levels, GenAI use, and goal orientation, reflecting that GenAI effects are filtered through both cognitive resources and motivational systems entrepreneurs bring to the human-AI interface (Vanneste & Puranam, 2025). Our research question is: *How do initial entrepreneurial competencies and motivational goal orientations interact to determine developmental outcomes of GenAI reliance?* Our empirical results reveal three distinct configurations. First, GenAI functions as a *force multiplier* for entrepreneurs, combining high baseline Individual Entrepreneurial Orientation (IndEO) with a learning goal orientation: these individuals leverage GenAI for genuine skill development rather than task completion. Second, GenAI triggers *competence erosion* for prove-oriented entrepreneurs with high baseline competencies, who use GenAI as a shortcut that bypasses the effortful practice of sustaining their skills. Third, GenAI plays a *paradoxical dual role* for avoidance-oriented entrepreneurs: serving as a safety net that enables engagement for those with low baseline competencies, yet functioning as a barrier to growth for those with high baselines who use it defensively. Together, these findings establish that GenAI's impact on entrepreneurial development is fundamentally contingent on the alignment between starting competence and underlying motivational orientation.

2. Theoretical Framework

Entrepreneurial action under uncertainty requires sophisticated metacognitive processes, the capacity to monitor, evaluate, and regulate one's own thinking. GenAI tools fundamentally alter this landscape by serving as external cognitive resources that can augment, supplement, or supplant internal cognitive processes (Choudhary et al., 2023; Lévesque et al., 2022). Entrepreneurial competence development, including creative self-efficacy, perspective-taking, and entrepreneurial orientation, requires deliberate practice and effortful engagement (Frese & Gielnik, 2023; Bandura, 1997). When GenAI circumvents effortful processing, it may produce short-term productivity gains at the cost of long-term skill acquisition (Sweller, 1988). This tension is particularly salient for entrepreneurship, where opportunity recognition depends on domain expertise developed through experiential learning (Corbett, 2005; 2007; Garbuio & Lin, 2021). We propose that goal

orientation, an individual's dispositional approach to achievement situations (VandeWalle, 1997), serves as the governing mechanism determining engagement depth at the entrepreneur-GenAI interface. Goal orientation theory distinguishes learning goal orientation (focused on mastery), prove goal orientation (focused on demonstrating competence), and avoidance goal orientation (focused on avoiding negative judgments). These orientations interact with GenAI use and baseline competence to produce distinct developmental trajectories.

2.1 The Force Multiplier Configuration (Learning Orientation)

Learning-oriented individuals approach GenAI with intrinsic motivation to develop competence. For these entrepreneurs, GenAI serves as a coach expanding the possibility space for exploration and providing rich feedback for iterative improvement. The mechanism operates through enhanced metacognitive engagement: learning-oriented entrepreneurs are more likely to critically evaluate GenAI outputs, compare them against their own reasoning, iterate on prompts to deepen understanding, and integrate GenAI-generated insights into existing knowledge structures (Chalmers et al., 2021; Cszasz et al., 2024). This aligns with research on entrepreneurial mindset development emphasizing that growth occurs through cycles of experimentation, reflection, and adaptation (Lynch & Corbett, 2023). We theorize this force multiplier effect is most pronounced among entrepreneurs with higher baseline competencies. Individuals with high IndEO (Clark et al., 2024; Wales et al., 2023) possess the proactive disposition, risk tolerance, and innovative mindset necessary to leverage GenAI for genuine exploration. When combined with a learning orientation, these entrepreneurs use GenAI not merely to complete tasks but to push the boundaries of their understanding, treating GenAI outputs as starting points for deeper inquiry.

H1: GenAI use is associated with enhanced competence for nascent entrepreneurs with high baseline competencies and high learning orientation.

2.2 The Erosion Configuration (Prove Orientation)

Prove-oriented individuals may approach GenAI with extrinsic motivation to demonstrate competence and achieve positive outcomes efficiently. For these nascent entrepreneurs, GenAI represents an efficiency tool that can generate high-quality outputs without requiring effortful cognitive processing that might expose competence gaps. The mechanism operates through cognitive offloading: prove-oriented entrepreneurs are more likely to accept GenAI outputs at face value, minimize iteration that might reveal uncertainty, and prioritize outcome quality over learning process (Lindebaum & Fleming, 2024). This represents a form of "algorithmic management" of one's own learning, where technology shapes behavior in ways that may undermine genuine development (Butler & Spoelstra, 2025). Critically, such offloading disrupts feedback loops necessary for skill development. When entrepreneurs outsource cognitive labor to GenAI without engaging in deep processing, they bypass productive struggles that drive learning. We theorize this detrimental effect is most pronounced among entrepreneurs with higher baseline competencies. High-competence, prove-oriented individuals have the most to "protect" reputationally and may use GenAI most extensively to maintain performance advantage without typical effort. The very entrepreneurs who appear most capable become most vulnerable to skill degradation because GenAI provides a seductive alternative to continued effortful practice (Lindebaum, 2024).

H2: GenAI use is associated with diminished competence specifically for nascent entrepreneurs with high baseline competence and high prove orientation.

2.3 The Safety Net/Barrier Configuration (Avoidance Orientation)

Avoidance-oriented individuals are primarily motivated to avoid negative judgments about competence (VandeWalle, 1997). Unlike prove-oriented individuals who seek positive evaluations, avoidance-oriented entrepreneurs focus on *not appearing incompetent*, leading them to withdraw from situations that might expose skill deficits (Elliot & Church, 1997). We theorize GenAI plays a dual, paradoxical role for these entrepreneurs, functioning as either a safety net enabling engagement or a barrier deepening withdrawal, depending on baseline competence level. For avoidance-oriented entrepreneurs with *low* baseline competencies, GenAI may serve as a psychological safety net. These individuals need developmental experiences but withdraw from challenging situations that would foster growth (Crosina et al., 2024). GenAI resolves this dilemma by providing low-stakes exploration, entrepreneurs can rehearse ideas or explore perspectives without social exposure. The technology creates psychological distance from failure: shortcomings can be attributed to the tool rather than personal inadequacy (Glikson & Woolley, 2020). Conversely, for avoidance-oriented entrepreneurs with *high* baseline competencies, GenAI may function as a barrier. These individuals have developed competencies

through prior effort but remain focused on avoiding exposure of limitations. GenAI offers an attractive escape: defensively outsourcing cognitive work to preserve reputation while avoiding growth-inducing struggle.

H3a: GenAI use is associated with *enhanced* competence development for nascent entrepreneurs with *low* baseline competence and high avoidance orientation (safety net effect).

H3b: GenAI use is associated with *diminished* competence development for nascent entrepreneurs with *high* baseline competence and high avoidance orientation (barrier effect).

3. Method

We employed a quasi-experimental pre-post design with non-equivalent control groups, comparing nascent entrepreneurs in which GenAI was integrated into entrepreneurial tasks (treatment) with those without GenAI use (control). The sample (N=201) consists of nascent entrepreneurs from a university context engaged in early-stage venture creation. This context also allows us to examine whether standard entrepreneurship training remains effective in an AI-enabled environment (Oosterbeek et al., 2010).

3.1 Measures

Our pre-test and post-test measures include creative self-efficacy (Tierney & Farmer, 2004), entrepreneurial self-efficacy, perspective-taking and empathetic concern (Davis, 1983), and Individual Entrepreneurial Orientation (Clark et al., 2024). During the pre-test survey, we used established scales to determine individual goal orientation, categorizing participants into learning, prove, and avoidance orientations (VandeWalle, 1997). GenAI use is a binary measure taking one if nascent entrepreneurs were in the cohort that allowed and encouraged GenAI use for completing early-stage venture creation activities (brainstorming, business model, MVP) and zero otherwise.

4. Results

Table 2 presents descriptive statistics and correlations for all study variables. Table 3 presents regression results testing the three-way interaction between baseline competencies, GenAI use, and learning orientation. The hypothesized force multiplier effect received significant support for Individual Entrepreneurial Orientation (IndEO). The three-way interaction term (GenAI × Learning Orient × IndEO pre-test) was positive and significant ($\beta = 0.347$, $p < .05$), indicating GenAI use enhances IndEO development specifically for entrepreneurs combining high baseline entrepreneurial orientation with high learning orientation. For entrepreneurs with high learning orientation and high baseline IndEO, GenAI use produces an upward trajectory in post-test IndEO scores. In contrast, entrepreneurs with high baseline IndEO but low learning orientation show a negative slope when using GenAI, suggesting that without a learning mindset, even initially capable entrepreneurs may experience competence stagnation, confirming that learning orientation fundamentally alters whether GenAI serves as a developmental accelerator or impediment. H2 received strong support across multiple competency domains. For creative self-efficacy, the three-way interaction (GenAI × Prove Orient × Creative SE pre-test) was negative and highly significant ($\beta = -0.246$, $p < .01$), indicating GenAI use significantly erodes creative self-efficacy for entrepreneurs who start with high creative confidence but harbor a prove orientation. The erosion effect extended to perspective-taking ability. The three-way interaction (GenAI × Prove Orient × Perspective pre-test) was negative and significant ($\beta = -0.224$, $p < .01$). Table 5 presents results testing safety net (H3a) and barrier (H3b) effects. For perspective-taking, the three-way interaction was negative and marginally significant ($\beta = -0.165$, $p < .10$), suggesting a barrier effect where GenAI impedes perspective-taking development for high-baseline, avoidance-oriented entrepreneurs. This domain-specific duality supports our proposition that avoidance orientation's effects depend on whether competency requires interpersonal risk-taking (safety net) versus authentic emotional engagement (barrier).

5. Contributions and Discussion

5.1 Theoretical Contribution 1: Configuration-Contingent View of AI's Role

This study introduces a novel human-GenAI cognitive engagement framework considering a three-way interaction between an entrepreneur's baseline competence, GenAI usage, and goal orientation. Our framework specifies conditions under which GenAI use leads to capability growth versus decline, rather than assuming uniform effects. This integrative model bridges goal orientation theory with entrepreneurial cognition, offering a configuration-contingent view of technology's role in entrepreneurial development.

5.2 Theoretical Contribution 2: The "Dark Side" of Cognitive Offloading

Our research demonstrates a trade-off suggesting GenAI's ability to turbocharge task completion can lead entrepreneurs to skip the struggle and practice needed for deep learning, resulting in competence stagnation over time. By articulating this efficiency-learning paradox, we align with and extend emerging discussions in management education warning against overreliance on assistive technologies. This provides theoretical explanation for why faster is not always better in skill development.

5.3 Theoretical Contribution 3: Baseline Competence as Counterintuitive Boundary Condition

Our research underscores initial skill level as a crucial and counterintuitive boundary condition. GenAI most enhances capability when high initial competence pairs with learning orientation, creating a "force multiplier" effect. Conversely, nascent entrepreneurs with high competence but prove-oriented mindset experience the greatest skill erosion, a paradox where those appearing most capable are actually most vulnerable to cognitive offloading. This challenges assumptions that high-skill individuals might be immune to AI's developmental drawbacks. Our study suggests that having entrepreneurs use GenAI tools in a vacuum is insufficient and can be detrimental; mentors, coaches, and educators must impart the "how" of deep engagement to ensure entrepreneurs use tools successfully. This study informs "GenAI-savvy" training to prioritize learning orientation over performance-validation to prevent nascent entrepreneurs from using GenAI as a crutch and experience skill degradation.

Ethics Declaration

Ethical clearance was obtained in line with the IRB guidelines.

AI Declaration

Grammarly AI was used for proofreading the paper.

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Table 2. Descriptive Statistics and Correlations

#	Variables	Mean	Std.Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Creative SE (post-test)	33.629	7.126																			
2	Ent SE (post-test)	22.114	3.482	0.417																		
3	Perspective (post-test)	20.272	2.964	0.391	0.261																	
4	Empathy (post-test)	9.709	3.776	0.162	-0.039	0.314																
5	IndEO (post-test)	4.430	0.825	0.434	0.470	0.270	0.018															
6	GenAI (1=Yes)	0.605	0.490	-0.056	-0.079	0.050	0.015	0.053														
7	Creative SE (pre-test)	33.975	7.686	0.677	0.293	0.269	0.126	0.316	-0.011													
8	Ent SE (pre-test)	24.964	3.914	0.322	0.597	0.177	-0.028	0.363	-0.078	0.317												
9	Perspective (pre-test)	19.587	3.744	0.260	0.107	0.540	0.263	0.101	0.010	0.259	0.198											
10	Empathy (pre-test)	9.435	4.270	0.080	-0.025	0.313	0.676	0.049	0.000	0.171	-0.049	0.408										
11	IndEO (pre-test)	4.490	0.913	0.311	0.479	0.137	-0.060	0.588	-0.019	0.323	0.565	0.089	-0.056									
12	Learning Orient	5.888	0.827	0.287	0.197	0.264	0.141	0.258	-0.061	0.309	0.314	0.446	0.234	0.287								
13	Prove Orient	4.737	1.193	0.070	-0.047	-0.012	0.014	-0.090	-0.021	0.071	0.141	0.110	0.004	0.031	0.180							
14	Avoidance Orient	4.849	0.984	-0.022	-0.169	0.091	0.254	-0.119	0.002	-0.054	-0.124	0.124	0.232	-0.215	-0.049	0.495						
15	Gender (male = 1)	0.565	0.497	0.059	0.103	-0.162	-0.242	0.035	-0.028	0.005	0.114	-0.213	-0.276	0.115	-0.047	0.042	-0.148					
16	Business Training	1.320	0.819	-0.129	-0.016	0.020	0.042	-0.065	0.016	-0.120	-0.081	-0.017	0.113	-0.124	0.021	0.065	0.077	0.023				
17	Student Location	0.880	0.355	0.006	0.011	0.029	0.019	0.056	-0.014	-0.110	0.019	0.089	0.130	-0.095	-0.029	-0.034	0.052	0.016	0.167			
18	Cognitive AI	4.001	0.840	0.095	0.068	0.146	0.160	0.096	0.001	0.098	0.216	0.264	0.099	0.120	0.317	0.060	0.023	0.065	0.001	0.059		
19	Affective AI	3.370	0.859	0.146	0.158	0.133	0.086	0.196	0.030	0.061	0.276	0.142	-0.018	0.182	0.232	0.076	-0.022	0.104	-0.001	0.012	0.700	
20	Behavioral AI	2.965	0.977	0.134	0.160	0.181	0.067	0.165	0.067	0.064	0.223	0.151	-0.010	0.154	0.193	-0.003	-0.040	0.213	0.080	0.060	0.620	0.754

N= 201, correlations above .200 are significant

Table 3: Baseline Competence, Learning Orientation, and GenAI use on Competence Development.

Variables	Creative SE (post-test)	Ent SE (post-test)	Perspective (post-test)	Empathy (post-test)	IndEO (post-test)
GenAI (1=Yes)	-31.930 (26.660)	4.663 (17.960)	8.755 (14.73)	-4.969 (8.04)	8.742* (4.574)
Learning Orient	-7.012** (3.473)	0.041 (2.200)	1.715 (2.044)	-1.166 (1.16)	1.080* (0.647)
Prove Orient	0.098 (0.387)	-0.317 (0.207)	-0.205 (0.191)	-0.078 (0.213)	-0.120** (0.048)
Avoidance Orient	0.131 (0.457)	-0.117 (0.249)	0.196 (0.222)	0.339 (0.257)	0.086 (0.059)
GenAI * Learning Orient	5.095 (4.392)	-2.216 (3.017)	-0.844 (2.500)	0.715 (1.345)	-1.410* (0.749)
Creative SE (pre-test)	-0.833 (0.663)				
GenAI * Creative SE (pre-test)	0.904 (0.835)				
Learning Orient * Creative SE (pre-test)	0.235** (0.108)				
GenAI * Learning Orient * Creative SE (pre-test)	-0.146 (0.135)				
Ent SE (pre-test)		0.192 (0.567)			
GenAI * Ent SE (pre-test)		-0.084 (0.752)			
Learning Orient * Ent SE (pre-test)		0.024 (0.093)			
GenAI * Learning Orient * Ent SE (pre-test)		0.069 (0.124)			
Perspective (pre-test)			1.102* (0.659)		

Variables	Creative SE (post-test)	Ent SE (post-test)	Perspective (post-test)	Empathy (post-test)	IndEO (post-test)
GenAI * Perspective (pre-test)			-0.683 (0.781)		
Learning Orient * Perspective (pre-test)			-0.101 (0.107)		
GenAI * Learning Orient * Perspective (pre-test)			0.084 (0.130)		
Empathy (pre-test)				0.336 (0.695)	
GenAI * Empathy (pre-test)				-0.096 (0.829)	
Learning Orient * Empathy (pre-test)				0.032 (0.115)	
GenAI * Learning Orient * Empathy (pre-test)				0.028 (0.137)	
IndEO (pre-test)					1.956** (0.930)
GenAI * IndEO (pre-test)					-2.136** (1.066)
Learning Orient * IndEO (pre-test)					-0.231 (0.149)
GenAI * Learning Orient * IndEO (pre-test)					0.347** (0.173)
Control variables	yes	yes	yes	yes	yes
Constant	53.32** (21.16)	16.46 (13.22)	0.385 (12.47)	8.748 (6.899)	-4.677 (3.977)
F	11.34***	7.70***	5.84***	12.05***	7.80***
R-squared	0.514	0.417	0.352	0.528	0.42

N=201, control variables (omitted for brevity): Gender, Business Training, Student Location, Cognitive AI, Affective AI, Behavioral AI

Table 4: Baseline Competence, Prove Orientation, and GenAI use on Competence Development.

Variables	Creative SE (post-test)	Ent SE (post-test)	Perspective (post-test)	Empathy (post-test)	IndEO (post-test)
GenAI (1=Yes)	-39.96*** (14.610)	-19.22* (9.800)	-16.46** (6.357)	-6.385 (3.967)	-2.705 (2.030)
Learning Orient	0.748 (0.517)	0.267 (0.275)	0.106 (0.262)	-0.102 (0.284)	0.140** (0.065)
Prove Orient	-4.074 (2.535)	-1.679 (1.323)	-2.006* (1.071)	-0.578 (0.601)	-0.273 (0.283)
Avoidance Orient	0.229 (0.451)	-0.209 (0.248)	0.292 (0.214)	0.485* (0.250)	0.069 (0.059)
GenAI * Prove Orient	7.993*** (3.046)	2.480 (2.051)	4.131*** (1.357)	1.434* (0.827)	0.562 (0.395)

Variables	Creative SE (post-test)	Ent SE (post-test)	Perspective (post-test)	Empathy (post-test)	IndEO (post-test)
Creative SE (pre-test)	-0.044 (0.352)				
GenAI * Creative SE (pre-test)	1.214*** (0.412)				
Prove Orient * Creative SE (pre-test)	0.128* (0.072)				
GenAI * Prove Orient * Creative SE	-0.246*** (0.085)				
Ent SE (pre-test)		0.070 (0.249)			
GenAI * Ent SE (pre-test)		0.800** (0.385)			
Prove Orient * Ent SE (pre-test)		0.061 (0.051)			
GenAI * Prove Orient * Ent SE (pre-test)		-0.108 (0.080)			
Perspective (pre-test)			0.001 (0.252)		
GenAI * Perspective (pre-test)			0.913*** (0.315)		
Prove Orient * Perspective (pre-test)			0.101* (0.053)		
GenAI * Prove Orient * Perspective (pre-test)			-0.224*** (0.066)		
Empathy (pre-test)				0.372 (0.274)	
GenAI * Empathy (pre-test)				0.624* (0.362)	
Prove Orient * Empathy (pre-test)				0.043 (0.057)	
GenAI * Prove Orient * Empathy (pre-test)				-0.139* (0.076)	
IndEO (pre-test)					0.318 (0.330)
GenAI * IndEO (pre-test)					0.620 (0.431)
Prove Orient * IndEO (pre-test)					0.036 (0.060)
GenAI * Prove Orient * IndEO (pre-test)					-0.124 (0.083)
Controls	yes	yes	yes	yes	Yes
Constant	26.63** (12.6)	21.26*** (6.382)	18.55*** (5.27)	3.466 (3.31)	2.047 (1.545)

Variables	Creative SE (post-test)	Ent SE (post-test)	Perspective (post-test)	Empathy (post-test)	IndEO (post-test)
F	11.9***	7.76***	6.90***	11.31***	7.62***
R-squared	0.526	0.419	0.39	0.512	0.415

N=201, control variables (omitted for brevity): Gender, Business Training, Student Location, Cognitive AI, Affective AI, Behavioral AI

Table 5: Baseline Competence, Avoidance Orientation, and GenAI use on Competence Development.

Variables	Creative SE (post-test)	Ent SE (post- test)	Perspective (post-test)	Empathy (post-test)	IndEO (post- test)
GenAI (1=Yes)	-13.450 (20.25)	4.735 (13.67)	-10.76 (10.04)	7.692 (4.654)	-2.572 (2.596)
Learning Orient	0.792 (0.518)	0.267 (0.277)	0.233 (0.266)	-0.0034 (0.283)	0.161** (0.065)
Prove Orient	-0.026 (0.386)	-0.321 (0.206)	-0.238 (0.18)	-0.227 (0.206)	-0.122** (0.048)
Avoidance Orient	1.129 (3.196)	1.306 (1.819)	-0.457 (1.401)	1.685** (0.774)	-0.507 (0.367)
GenAI * Avoidance Orient	2.425 (4.001)	-2.302 (2.637)	2.52 (2.048)	-1.657 (1.004)	0.479 (0.489)
Creative SE (pre-test)	0.590 (0.464)				
GenAI * Creative SE (pre-test)	0.545 (0.564)				
Avoidance Orient * Creative SE (pre-test)	-0.001 (0.091)				
GenAI * Avoidance Orient * Creative SE (pre-test)	-0.107 (0.111)				
Ent SE (pre-test)		0.583 (0.364)			
GenAI * Ent SE (pre-test)		-0.051 (0.520)			
Avoidance Orient * Ent SE (pre-test)		-0.039 (0.068)			
GenAI * Avoidance Orient * Ent SE (pre-test)		0.061 (0.101)			
Perspective (pre-test)			0.13 (0.334)		
GenAI * Perspective (pre-test)			0.735 (0.481)		
Avoidance Orient * Perspective (pre-test)			0.063 (0.069)		
GenAI * Avoidance Orient * Perspective (pre-test)			-0.165*		

Variables	Creative SE (post-test)	Ent SE (post- test)	Perspective (post-test)	Empathy (post-test)	IndEO (post- test)
			(0.097)		
Empathy (pre-test)				0.947*** (0.334)	
GenAI * Empathy (pre-test)				-0.486 (0.432)	
Avoidance Orient * Empathy (pre-test)				-0.087 (0.071)	
GenAI * Avoidance Orient * Empathy (pre-test)				0.151* (0.089)	
IndEO (pre-test)					-0.144 (0.415)
GenAI * IndEO (pre-test)					0.538 (0.533)
Avoidance Orient * IndEO (pre-test)					0.121 (0.075)
GenAI * Avoidance Orient * IndEO (pre- test)					-0.095 (0.101)
Controls	yes	yes	yes	yes	yes
Constant	2.209 (16.92)	6.684 (9.599)	13.67** (6.851)	-3.971 (3.961)	4.217** (1.982)
F	11.34***	7.83***	6.40***	11.24***	7.63***
R-squared	0.514	0.421	0.373	0.511	0.415

N=201, control variables (omitted for brevity): Gender, Business Training, Student Location, Cognitive AI, Affective AI, Behavioral AI