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Generative Artificial Intelligence and Ethicality in Entrepreneurs' Creativity

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Abstract

We explore the complex relationship between generative artificial intelligence (G-AI) and the ethical aspects of creative activities. Based on the dual concepts of attribution theory and entrepreneurs' self-regulation, we examine how G-AI impacts entrepreneurs' creativity, including unethical creativity, and those displaying traits linked to the 'dark side' of the human personality. Using data from India and Bangladesh, we test the core hypothesis that G-AI increases creativity within an entrepreneurial context. Contrary to prevailing narratives about G-AI's ability to enhance human creativity, our findings show that G-AI's direct influence on creativity is statistically insignificant. More importantly, our results highlight that G-AI use is positively related to unethical creativity—a form of innovation that breaches normative standards—especially among entrepreneurs with high levels of narcissistic and Machiavellian traits. Our study advances attribution theory and self-regulation by revealing how entrepreneurs' internal conflicts, such as the tension between aspirational creativity and opportunistic self-interest, interact with their self-control to produce unethical creativity. We offer important insights into how G-AI can be employed responsibly and ethically in entrepreneurial venturing.

Keywords Artificial intelligence · Creativity · Unethical creativity · Machiavellianism · Psychopathy · Narcissism

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Introduction

Generative artificial intelligence (G-AI) is a subset of artificial intelligence that generates information by leveraging advanced machine learning and deep learning (Grimes et al., 2023). Scholars point to the potential of G-AI to enhance creativity (Shepherd & Majchrzak, 2022), suggesting it may lead entrepreneurs to become more creative (Chalmers et al., 2021). G-AI can predict trends and forecast customer preferences through data-driven insights (Kaplan & Haenlein, 2019), ranging from large language models like ChatGPT to image and code generators that enable entrepreneurs to ideate, iterate, and execute creative concepts more broadly than before. For instance, entrepreneurs can use G-AI to generate novel product ideas, simulate customer personas, test marketing narratives, or visualize branding assets, thereby expanding both the scope and speed of early-stage ideation (Chalmers et al., 2021). G-AI can also function as a tool to lower the cost of experimentation and enable entrepreneurs to explore a wider set of possibilities than would be feasible manually. This co-creation process supports divergent thinking and could enable entrepreneurs to move fluidly between abstract ideation and concrete implementation (McGuire

et al., 2024). In this sense, G-AI could serve as a "creativity partner" by assisting entrepreneurs to overcome cognitive fixation and limited domain knowledge (Kaplan & Haenlein, 2019).

However, even as G-AI may support creative problem-solving, entrepreneurs' use of it can become ethically questionable, ranging from data privacy breaches to deceptive practices that violate trust (Puntoni et al., 2021). A general example of unethical creative behavior is Enron's former CFO, Andrew Fastow, whose actions and misconduct were unethical yet highly innovative as he creatively found loopholes in finance and accounting (Teather, 2004). In the context of AI, an example of how individuals can distort an algorithm is the chatbot Tay, which, within hours of its launch, was taught politically incorrect expressions (Amesh et al., 2014). Köbis et al. (2025) examine whether the use of G-AI, such as GPT-4o, could lead individuals to delegate tasks (i.e., tax evasion) unethically. The findings demonstrated that individuals' delegation instructions could lead to unethical behavior in 50–85% of cases. Hence, individuals found it easier to justify their actions by claiming ignorance of how the G-AI would interpret these instructions, which is why Köbis et al. (2025) urge scholars and users to consider the moral aspects of individuals' creativity when employing G-AI.

Unethical creativity is defined as a "novel and innovative behavior that violates widely held moral norms" (Mai et al., 2022, p. 114). This extends beyond the usual understanding of unethical behavior as it involves creatively circumventing ethical norms or rules rather than violating them directly. G-AI has the potential to increase these instances. Yet, existing research has largely focused on the technical affordances and efficiency effects of G-AI, without questioning how entrepreneurs make sense of their own G-AI-co-created behaviors, especially when creativity veers into ethically ambiguous territory (Glikson & Woolley, 2020). This line of research is presently silent, and the dual nature of G-AI's influence on creativity, *ethical or unethical*, warrants urgent theoretical and empirical investigations. To address this knowledge deficit, we ask our first research question: *How does G-AI usage influence entrepreneurs' creativity (ethical or unethical)?*

To provide a cohesive explanatory logic for this research question, we draw on attribution theory (Heider, 1958; Muschetto & Siegel, 2021; Weiner, 1986, 2018). Attribution theory posits that individuals interpret events by assigning internal (self-driven) or external (context-driven) causes (Czaja & Röder, 2020; Mandl et al., 2016; Mantere et al., 2013; Pardo & Alfonso, 2017). In entrepreneurship, this attributional process becomes particularly salient because entrepreneurs rely heavily on self-perception to sustain their sense of agency (Krueger, 2007; Murnieks et al., 2014; Theoharakis et al., 2021). When an entrepreneur produces successful outcomes using G-AI, they may attribute these results internally to their own creativity, vision, and capabilities. However, when outcomes are ethically questionable, the same individual may externalize responsibility, attributing negative consequences to G-AI systems rather than to their own moral judgment (Köbis et al., 2025). For example, a recent study found that individuals cheated more when using AI systems under conditions where the AI could deduce the cheating strategy implicitly, and the overall rate of unethical outcomes was significantly higher with AI involvement than without (Köbis et al., 2025). These findings reinforce our argument: simply making an unethical act *easier* is not the sole factor; moral distancing and altered attributions play a decisive role in increasing unethical intentions. AI adds an extra degree of separation between the entrepreneur and the harmful act, making it easier to rationalize and carry out. This attributional asymmetry reflects a bias in which entrepreneurs see themselves as competent and ethical while distancing themselves from the moral implications of their AI decisions (Tong et al., 2021). By grounding in attribution theory, we intend to offer a unified account of how entrepreneurs make sense of their G-AI–co-created actions.

The boundaries of ethical behavior can blur with G-AI, as not all entrepreneurs use tools responsibly. Human behavior varies based on personality traits, affecting how they perceive and apply technology (Lebuda et al., 2021) and what they value or consider acceptable (Cesinger et al., 2023). What is morally repugnant to one may be seen as legitimate to others based on the "*dark triad*" of personality traits (hereafter, DPTs) associated with entrepreneurs: *narcissism*, *Machiavellianism*, and *psychopathy* (Hmieleski & Lerner, 2016). The existing literature is unexpectedly silent in defining the boundary conditions of entrepreneurial actions (Brownell et al., 2023; Hmieleski & Lerner, 2016; Klotz & Neubaum, 2016). Our study emphasizes the DPTs in entrepreneurship and G-AI usage as a strategic choice, reflecting a shift toward understanding the complex psychological underpinnings of entrepreneurial behavior in an era of technological revolution – an area that needs theoretical development and is starting to gain attention in entrepreneurship research (Brownell et al., 2023). Hence, we address a second research question: *To what extent do DPTs moderate the relationship between G-AI usage and unethical creativity?*

Our study offers two novel contributions to theory. First, the study presents a theoretical framing of the duality of G-AI usage in relation to ethical and unethical creativity grounded in attribution theory. However, empirically, we find that G-AI only increases unethical creativity, supporting the thesis that entrepreneurs may deliberately utilize the dark side of G-AI and then rationalize this as G-AI's fault. This observation aligns with the literature on G-AI that has recognized the dark side of AI whereby many AI systems today lack clear responsibility for outcomes and may amplify bias

(Mikalef et al., 2022). For entrepreneurship theories, it calls on scholars to consider the consequences of technology-enabled and technology-mediated entrepreneurial actions carefully and whether the ethical compass of entrepreneurs is destabilized by G-AI technology. Second, elaborating on why G-AI might destabilize the ethical behavior of entrepreneurs, we theorize the behavioral traits of entrepreneurs that influence this complex relationship, recognizing that it is imprudent to attribute unethical creativity solely to G-AI. This provides a theoretical advancement to attribution theory insofar as this theory, in isolation, inadequately addresses the role of personality traits. We utilize Bryant's (2009) self-regulation perspective to explain how each DPT might moderate the relationship between G-AI usage and unethical creativity. A critical threshold is hypothesized, beyond which the intensification of DPTs in entrepreneurs could shift the role of G-AI increasingly toward facilitating unethical creativity. For those with high levels of DPTs, their self-regulatory focus is skewed toward achieving personal success and power (Cesinger et al., 2023), potentially exacerbating the use of G-AI for unethical conduct. Human capacity for self-regulation is finite and, once depleted, can lead to a more pronounced expression of inherent personality traits (Mitchell et al., 2019), using G-AI as a means of gaining strategic advantages. Our new thesis and findings call on scholars to understand the nature of the human being and their agency to understand the ethical implications of G-AI usage in entrepreneurship.

These contributions provide a more complete understanding of how entrepreneurs' creativity and ethics are shaped by their engagement with G-AI tools. We position attribution theory as the core explanatory lens, showing how entrepreneurs reorient AI-generated outputs to support both self-enhancement and ethical distancing (Köbis et al., 2025; Tong et al., 2021). We explain how G-AI differs, enabling co-created creative outputs that are difficult to disentangle, thereby amplifying attributional ambiguity (Zeiser, 2024). Unlike earlier works that emphasize G-AI as an efficiency or decision support tool, we highlight how G-AI's generative nature fundamentally alters attribution dynamics, particularly when outputs are novel and difficult to trace (Glikson & Woolley, 2020). Moreover, whereas prior studies applied attribution theory to explain failure narratives, explanatory styles, or interpersonal judgments in entrepreneurship (Mantere et al., 2013; Pardo & Alfonso, 2017), our study extends the theory by examining attributional reorientation in the context of generative AI. We argue that the ambiguous authorship of AI-assisted outputs creates abundant ground for attributional bias: entrepreneurs may claim internal credit for creative successes while shifting blame for unethical outcomes onto external systems like G-AI. Importantly, we elaborate on this logic, theorizing that this self-serving attribution pattern is moderated by individual differences in DPTs and providing a new view of when entrepreneurs are most likely to ethically distance themselves from their G-AI-assisted conduct. This extends attribution theory into a rapidly evolving technological domain and provides a predictive framework for understanding ethical agency in human–AI co-creation.

Literature review, theory, and hypotheses

Creativity in entrepreneurship and G-AI

Creativity is the starting point for opportunity identification, novel idea generation, and innovation (Zhou, 2008). Entrepreneurs often navigate complex, uncertain, and rapidly evolving markets where traditional strategies may be inadequate or obsolete. In such scenarios, creativity is not just an asset but a necessity (Townsend & Hunt, 2019), essential for dealing with the uncertain outcomes of entrepreneurial activities. Entrepreneurs' strategic decision-making is rarely static either. Market conditions, competition, and technology are constantly in flux. Creativity complements adaptability and flexibility (Williams et al., 2021), positioning entrepreneurs to modify their strategies in response to external changes, often pre-emptively. While creativity is crucial, the most effective strategic decisions may come from balancing creativity and analytics (Groves et al., 2011). This integration enables the generation of innovative ideas while grounding them in data-driven analysis. As the creativity literature suggests, entrepreneurs should navigate this balance, harnessing creativity for innovation while relying on analytical tools and platforms, such as G-AI, to create value (Townsend & Hunt, 2019).

G-AI is not merely a tool but an active participant in the creative process, working in tandem with human insight and ingenuity (Viskova-Robertson, 2023). G-AI can complement human abilities, enabling a symbiotic relationship that yields more creative, novel outputs (Plastino & Purdy, 2018). While G-AI is still evolving, we have not reached the point where G-AI can exhibit general intelligence. Current G-AI systems are limited by their dependence on training data, lack of genuine reasoning, and their vulnerability to hallucinations, bias, and misinterpretation of context (Jones, 2025). Therefore, while G-AI demonstrates impressive functionality in analytical tasks, it does not yet possess the autonomy or generalizable intelligence required to operate independently. Thereby, the human agent plays a vital role working alongside G-AI to co-create novel solutions to address complex problems. It is the G-AI–human collaboration that drives much of the output from G-AI (Townsend & Hunt, 2019).

Attribution theory, creativity, and unethical creativity

Heider (1958), followed by Weiner (1986, 2018), developed attribution theory as a psychological framework that explains how individuals make sense of their actions and the events around them. Central to this theory is the concept of attribution paradoxes. Attribution paradoxes describe the tendency for individuals to preserve their self-esteem by attributing successes to their own efforts and failures to external factors (Breugst & Shepherd, 2017), denying responsibility for negative outcomes. It suggests that entrepreneurs engaging in unethical creative endeavors might blame G-AI to protect their self-image, especially in situations involving ethical responsibility where the blame for failure can be more easily shifted onto emerging technologies. When ethical lapses occur in the creative use of G-AI, such as breaching data privacy, manipulating consumer data using G-AI, manipulating outputs for deceptive gain, or producing unethical content, entrepreneurs may displace moral accountability onto the technology itself, rationalizing misconduct as a function of the system rather than their own intent (Köbis et al., 2025). This is akin to the self-serving bias (Dong & Bocian, 2024; Miller & Ross, 1975), where individuals attribute positive outcomes to their actions and negative outcomes to external factors. This dynamic aligns with the growing literature on the *dark side of AI*, which emphasizes that the same tools that enable innovation can also be exploited to circumvent responsibility, deceive stakeholders, or obscure authorship (Mikalef et al., 2022).

Baseline hypothesis: G-AI and creativity

Entrepreneurs are increasingly generating machine–human co-created outputs (Faulconbridge et al., 2023; McGuire et al., 2024). Recent studies suggest that G-AI enables hybrid forms of creativity in which the boundaries between human and machine contributions are increasingly entangled (Chalmers et al., 2021; Raisch & Fomina, 2025). Unlike earlier digital tools such as search engines, which served primarily as passive instruments, G-AI systems actively contribute to ideation and execution processes (Raisch & Fomina, 2025), often in ways that make it difficult to disentangle who generated what (Shepherd & Majchrzak, 2022). This fusion of human and machine agency creates novel attributional ambiguity (Zeiser, 2024): when outcomes are successful or ethically questionable, entrepreneurs may struggle to assign, or selectively choose to assign, credit or blame. It is this ambiguous authorship and co-creation dynamic, more than just interactive search, that fundamentally distinguishes G-AI and leads to attribution distortions. In this way, attribution theory explains why G-AI is more than just a helpful tool; it acts as a catalyst for creativity by strengthening entrepreneurs' confidence in their own abilities (Chalmers et al., 2021; Shepherd & Majchrzak, 2022).

In human and G-AI collaboration, the boundaries between the entrepreneur's input and the AI's output are often indistinct. This causal ambiguity makes it difficult for entrepreneurs to discern the true origin of creative ideas (Chalmers et al., 2021; Shepherd & Majchrzak, 2022). When the AI produces fluent, novel, or contextually appropriate content in response to user prompts, entrepreneurs may misattribute these results due to only their own abilities, particularly when the AI's contributions are opaque and difficult to disentangle (Tong et al., 2021). Attribution theory suggests that in situations where causality is ambiguous, individuals are more likely to adopt self-serving explanations, claiming credit for successful outcomes while deflecting blame for negative ones (Czaja & Röder, 2020; Köbis et al., 2025; Weiner, 1986). This ambiguity allows entrepreneurs to consider G-AI as a background tool, reinforcing their belief in their own creative agency.

Grounded in attribution theory, our baseline hypothesis posits that entrepreneurs' creative achievements result from a synergistic partnership between their cognitive abilities and G-AI's potential—a partnership in which G-AI enhances creativity. Because G-AI outputs are ambiguous and difficult to disentangle (Dong & Bocian, 2024), entrepreneurs are predisposed to internalize success as only being self-generated (Tong et al., 2021). Thus, an attributional lens is particularly well suited to explain why entrepreneurs who use G-AI may attribute the co-created creative successes to themselves and their own ingenuity. In entrepreneurial contexts, this self-serving bias is especially salient because success or failure is closely tied to identity and personal reputation (Murnieks et al., 2014; Theoharakis et al., 2021). Creativity is central to the entrepreneur's identity (Krueger, 2007; Theoharakis et al., 2021). They may tend to attribute success to their skills in crafting prompts, selecting among AI-generated alternatives, or integrating AI outputs into broader venture strategies. This internal attribution reinforces their creative potential (Chalmers et al., 2021). When individuals attribute success to their own ability or effort, they experience heightened self-confidence, which bolsters confidence and motivates more creative efforts (Kasof, 1995; Shepherd & Majchrzak, 2022). With G-AI, the entrepreneur's self-serving attribution establishes a positive feedback loop: successful outcomes assisted by the tool are internalized, encouraging even more involvement in creative activities. This logic builds on Amabile's (2020) observation that human–AI interactions can yield creative breakthroughs precisely because individuals perceive themselves as active agents in the process. Thus, we hypothesize:

H1: G-AI usage positively influences creativity

G-AI and unethical creativity

The same ambiguity that inflates internal attributions for successful outcomes also enables moral distancing when creative results are ethically questionable. Entrepreneurs may rationalize misconduct, such as producing deceptive content or manipulating outputs, as originating from the G-AI itself, thereby shielding their self-concept and avoiding ethical responsibility (Dong & Bocian, 2024; Köbis et al., 2025; Mikalef et al., 2022). This shifting attribution of accountability highlights the mechanism through which both ethical and unethical creativity can coexist within G-AI use, depending on how individuals orient authorship.

Divergent thinking and cognitive flexibility as features of general creativity equip entrepreneurs to ideate novel methods for sidestepping ethical norms in ways that enable them to rationalize and reconceptualize their deviant actions as justifiable within their moral framework (Qin et al., 2020, 2022). G-AI can amplify boundary-pushing behavior by expanding entrepreneurs' cognitive bandwidth and providing a layer of plausible deniability (Raisch & Fomina, 2025). As shown in the dark side of AI literature, entrepreneurs may delegate ethically questionable tasks, such as manipulating messages or bypassing social norms (Dong & Bocian, 2024; Mikalef et al., 2022; Wach et al., 2023). This allows users to offload blame onto the system, especially when outcomes are ambiguous or controversial. In line with attribution theory, individuals are more likely to externalize moral accountability when a third party (in this case, AI) can be positioned as the proximate cause (Köbis et al., 2025). Thus, the presence of G-AI may shift entrepreneurs' ethical boundaries, not simply by making transgressions easier, but by reshaping how accountability is distributed across human–machine interactions.

Unethical creativity represents a distinct form of behavior that intentionally violates or circumvents ethical standards and societal norms (Mai et al., 2022). Creativity itself is ethically agnostic (Mai et al., 2022); it is associated with positive and noble outcomes (Keem et al., 2018) but can also manifest in ethically questionable actions (Gino & Ariely, 2012). What renders it ethical or unethical is the intent and context of its application. In entrepreneurial settings, this distinction becomes critical: G-AI can be deliberately used not only to generate breakthrough ideas but also to devise manipulative marketing, fabricate content, or bypass regulatory scrutiny, all under the guise of innovation. Drawing on the dark side of AI literature (Mikalef et al., 2022; Wach et al., 2023), we contend that G-AI's opacity makes it especially susceptible to misuse. Entrepreneurs may intentionally participate in ethically questionable conduct when utilizing G-AI, as responsibility can be attributed to the G-AI, safeguarding their self-image as legitimate and visionary (Köbis et al., 2025). Attribution theory helps explain this

mechanism: when outcomes are morally ambiguous, entrepreneurs may selectively displace ethical responsibility for transgressions onto G-AI (Shaver et al., 2001). This ability to exploit G-AI's affordances while sidestepping moral accountability is central to our thesis, highlighting how G-AI can serve both as a catalyst for innovation and as a tool for ethical evasion.

Consistent with Bandura's (1999) notion of moral disengagement, this attributional reorientation serves as a mechanism through which entrepreneurs can distance themselves from unethical outcomes (Baron et al., 2015). As G-AI influences entrepreneurial decision-making, the intertwining of G-AI and the entrepreneur becomes more pronounced (Kane et al., 2021), shaping both outcomes and moral judgments (Verbeek, 2014). This hybridization creates causal ambiguity over who bears responsibility for ethical reasoning, *the human* or *the machine*, making moral accountability increasingly diffuse (Glikson & Woolley, 2020). Scholars of the dark side of AI argue that such ambiguity is not incidental but an enabling feature of AI's design that can be exploited to justify ethically questionable outcomes (Dong & Bocian, 2024; Mikalef et al., 2022). G-AI does not merely complicate moral responsibility; it opens the structural space for entrepreneurs to deflect blame or disengage morally.

Biases in G-AI algorithms and the lack of ethical considerations in G-AI systems (Niu & Mvondo, 2024) compound challenges in controlling human impulses that may be exploited for entrepreneurial advantage. Empirical work indicates that people using G-AI can experience lower perceived personal accountability and can more readily deflect responsibility to the system (Köbis et al., 2025). The fusion of human and G-AI decision-making blurs accountability (Mittelstadt et al., 2016), making it difficult to pinpoint responsibility for decisions and actions (Sullivan & Wamba, 2022). This ambiguity functions as an attributional buffer because entrepreneurs externalize blame toward G-AI when outcomes are questionable but internalize credit when results are favorable (Köbis et al., 2025; Miller & Ross, 1975). This ambiguity may embolden entrepreneurs to act immorally, attributing unethical choices to G-AI influences. As entrepreneurs use G-AI, it can lead to behavior driven by entitlement and a desire for success, fostering dishonesty and deviance (Qin et al., 2020, 2022). Under pressures of high demands and high stakes, G-AI may pose the risk of steering entrepreneurs toward unethical creativity (Mai et al., 2022; Mitchell et al., 2018). According to attribution theory, the intertwining of human and G-AI creates a basis for engaging in and encouraging unethical creativity, as entrepreneurs can shift their responsibility toward the G-AI when their actions are questionable (Köbis et al., 2025). This dynamic mirrors the process observed in *H1,* but with reversed valence: where attributional reorientation may amplify creativity, it

also attenuates ethical restraint through externalization of blame.

We suggest that the lack of integration of ethical values in using G-AI (Cachat-Rosset & Klarsfeld, 2023; Niu & Mvondo, 2024), in conjunction with the potential for entrepreneurs to misuse G-AI to serve higher gains, produces a permissive moral context. Such amoral tendencies are strengthened by G-AI's role as a moral intermediary (De Freitas et al., 2023). In line with attribution theory, G-AI can serve as a convenient scapegoat for entrepreneurs (and any subsequent blame) for their actions (Shepherd & Majchrzak, 2022; Sullivan & Wamba, 2022), which prompts opportunities for unethical conduct. Entrepreneurs have a heightened need to preserve their moral self-image (Theoharakis et al., 2021), making this tendency even more pronounced. The difficulty in disentangling AI–human co-created outputs offers a convenient explanation for ethically ambiguous outcomes (Köbis et al., 2025). This attributional shifting aligns with the dark side of AI literature, which shows that individuals may exploit AI systems to distance themselves from moral consequences and rationalize misconduct (Dong & Bocian, 2024; Mikalef et al., 2022). When opportunity and pressure converge, G-AI may inadvertently encourage unethical creativity by acting as a moral buffer (Glikson & Woolley, 2020). The result is a self-protective cognitive bias that preserves moral self-image while enabling opportunistic ethical flexibility (Mandl et al., 2016; Mantere et al., 2013; Pardo & Alfonso, 2017). By attributing ethical lapses to G-AI, entrepreneurs are less constrained by moral norms, increasing the likelihood of engaging in unethical practices. Therefore, in contrast to its predicted positive role in fostering creativity, we hypothesize that G-AI also facilitates attributional displacement that reduces ethical accountability:

H2: G-AI usage positively influences unethical creativity

The moderating role of DPTs between G-AI usage and the unethical creativity relationship

As DPTs, narcissism, Machiavellianism, and psychopathy share a common tendency toward manipulation and control, and they are characterized by low agreeableness (Paulhus & Williams, 2002). These traits manifest distinctively: narcissism is defined by a need for external validation and a craving for a social spotlight; psychopathy is characterized by impulsivity, thrill-seeking, and a lack of empathy and remorse, often leading to aggressive behaviors (Spain et al., 2014), and Machiavellianism involves covert manipulation and a flexible moral compass (Christie & Geis, 2013; Furnham et al., 2013). DPTs are not binary states but exist on a continuum (Furnham et al., 2013), influencing various outcomes to differing degrees (Klotz & Neubaum, 2016).

We theorize that these traits can impact how entrepreneurs approach G-AI. For instance, Machiavellian entrepreneurs, driven by a need for success and power, might use G-AI for innovative solutions, exploiting opportunities for personal gain (McLarty et al., 2023; Zettler & Solga, 2013). Narcissistic entrepreneurs may leverage G-AI to enhance their status and achieve ambitious goals (Campbell & Foster, 2007), while psychopathic entrepreneurs could view G-AI as a strategic tool for domination and gaining a competitive advantage (Klotz & Neubaum, 2016). While often viewed negatively, these traits can have advantages: narcissists can emerge as charismatic leaders (Nevicka et al., 2011), Machiavellians are effective in resource acquisition (Jones & Paulhus, 2009), and psychopaths can balance antisocial tendencies with goal-oriented behaviors (Boddy, 2015). However, the positive aspects of DPTs necessitate self-regulation to control their downsides.

A self-regulation perspective of DPTs

Self-regulation is a process that involves setting personal goals, monitoring progress, and adjusting behavior to achieve outcomes (Zeidner et al., 2000). This process, initially conceptualized to include self-monitoring, self-evaluation, and self-reinforcement (Bryant, 2009), has been expanded to encompass receiving information, goal setting, and monitoring progress (Lex et al., 2022). Personality traits, which represent consistent patterns of thoughts and behaviors (Li et al., 2014), play a crucial role in an individual's self-regulatory ability (Hoyle & Gallagher, 2015). Entrepreneurs with heightened DPTs often struggle with self-regulation, especially in managing immoral or harmful impulses (Dahling et al., 2009). High levels of DPTs can lead to impaired emotional regulation and reduced impulse control (Uziel & Baumeister, 2017), making such entrepreneurs more prone to self-serving and opportunistic justifications of unethical conduct (Vincent & Kouchaki, 2016).

DPTs have been associated with different forms of creativity (Sordia et al., 2022). For example, narcissism has been linked to functional impulsivity, which may lead to novel ideas (Jones & Paulhus, 2011), and psychopathy is associated with unconventional thinking (Sordia et al., 2022). However, we hypothesize a critical threshold at which the intensification of DPTs in entrepreneurs could shift the role of G-AI from being a positive force enhancing creativity to a contributor to unethical creativity. Thus, our decision not to hypothesize the role of DPTs in the relationship between G-AI usage and creativity stems from a deeper consideration of the ethical dimensions of this relationship. Research by Cropley et al. (2008), Szabó et al. (2022), and Kapoor (2015) demonstrates that DPTs often correlate with negative or malevolent activities, such as unintentional harm or intentional damage. This aspect raises significant ethical

concerns, particularly regarding how low moral considerations inherent in DPTs could amplify the risk that G-AI disrupts ethical decision-making and behavior. Given this background, we are cautious about expecting DPTs to moderate the relationship between G-AI usage and creativity. Instead, we expect the influence of a high level of DPTs to moderate the use of G-AI more greatly toward ethically questionable or harmful outcomes.

The moderating role of Machiavellianism

Four attributes define Machiavellianism: inclination to neglect ethical norms and amorally exploit others to fulfill self-oriented outcomes; distrust of others and a cynical view of the intentions and motives of others; a desire for control, reducing the power of others, and for dominating interpersonal situations; and the desire for status and to obtain extrinsic indicators of success which drives them to be good at exploiting opportunities to maximize their profits (Christie & Geis, 2013; Dahling et al., 2009; Liu, 2008). Machiavellians participate in interpersonal manipulation and opportunistic behaviors to serve their self-interests (Castille et al., 2018). These individuals are characterized by their ability to be rational and calm in social interactions while cunningly manipulating the situation (Hurley, 2005). It is expected that at low to moderate levels, Machiavellian entrepreneurs can regulate their immoral or deviant damaging tendencies (Brownell et al., 2023) and leverage their self-confidence and intelligence productively when using G-AI.

However, as this DPT strengthens and reaches high levels of Machiavellianism, these entrepreneurs are expected to fail at regulating their immoral and unethical tendencies (Christie & Geis, 2013; Dahling et al., 2009). High Machiavellians may seek to gain an advantage without regard for morality (Myung & Choi, 2017). Such individuals associate with instability and cynicism and undertake unethical [creative] acts, such as lying, cheating, and sabotaging others, while pursuing their interests (Jones & Paulhus, 2009). Given this, it is plausible that G-AI usage in business may provide opportunities for individuals with high Machiavellianism to devise and employ creative yet unethical strategies to gain an edge over their competitors. At high levels of Machiavellianism, entrepreneurs' relentless pursuit of personal interests could exhaust their self-regulation resources, leading to increased unethical creativity. Therefore, for high Machiavellians, using G-AI may not simply mean an augmentation but a platform for deploying deceptive tactics and strategies. Thus:

H3: The relationship between G-AI usage and unethical creativity is moderated by Machiavellianism, such that the relationship between G-AI usage and unethical creativity will be strongest for entrepreneurs who exhibit high levels of Machiavellianism.

The moderating role of psychopathy

Psychopathy is characterized by a lack of guilt and empathy and the inability to understand and respond to the feelings of others. Psychopathic individuals have a marked propensity for taking advantage of others to fulfill their personal goals (Jonason & Krause, 2013). They exhibit a unique ability to be calm and focused in stressful conditions, a trait linked to low emotional reactivity (Hogan & Kaiser, 2005). In entrepreneurial contexts, psychopathy often manifests as an audacious form of confidence, often exhibited in risk-taking behaviors (Boddy et al., 2010). Notorious Silicon Valley Tech CEO Elizabeth Holmes and Uber's ex-CEO Travis Kalanick are known for their personalities, described as having an elaborate sense of self-assurance, poor control, devoid of empathy, remorse, or guilt, and pathological lying, rarely concerned about the repercussions of their actions (Brownell et al., 2023).

At low to moderate levels of psychopathy, we consider that entrepreneurs will be able to self-regulate their aggressive behaviors and destructive, disinhibited impulses. A unique aspect of psychopathy, psychopathic boldness, has been positively associated with creative activities (Sordia et al., 2022). This boldness often coincides with a risk-tolerant and venturesome attitude, traits beneficial for creative entrepreneurship (Runco, 2019). At high levels, we expect more dysfunctional creativity. We expect the moderation relationship to follow a trajectory where the relationship between G-AI usage and unethical creativity peaks for entrepreneurs demonstrating high levels of psychopathy. At high levels, psychopaths cannot regulate their hostile and aggressive impulses (Hare, 1991). This dysfunctional impulsivity stems from the inability of individuals with a strong psychopathy trait to exhibit self-control (Jones & Paulhus, 2011). The inability to inhibit antisocial behaviors, even when they contravene societal norms, leads highly psychopathic individuals to lack conscience and social responsibility (Boddy, 2015). This inability may become even more potent in the context of G-AI usage. Because G-AI lacks empathy and emotion (Li et al., 2017), and a psychopathic entrepreneur does as well (Jonason & Krause, 2013), extensive G-AI use should amplify the impact of high psychopathy on unethical creative actions. The inherent neutrality of G-AI provides a digital facade for highly psychopathic individuals, allowing them to carry out unethical creative actions without immediate social repercussions. Being devoid of human emotions, ethical dilemmas, and social norms, G-AI may unwittingly become a tool for these individuals to extend their antisocial behaviors (Botting, 2020). Consequently, we expect that entrepreneurs with high levels

of psychopathy are more prone to engaging in unethical creative actions while using G-AI. Thus:

H4: The relationship between G-AI usage and unethical creativity is moderated by psychopathy, such that the relationship between G-AI usage and unethical creativity will be strongest for entrepreneurs who exhibit high levels of psychopathy.

The moderating role of narcissism

Narcissism is associated with a sense of grandiosity, dominance, entitlement, and an obsession with success, yet a fragile sense of self- and low self-esteem (Lee & Ashton, 2005; Resick et al., 2009). Narcissistic entrepreneurs are motivated and disciplined (O'Boyle et al., 2012). It is exemplified by sturdy emotional tenacity but accompanied by an incessant need for self-admiration, arrogance, hostility toward external criticism, and a preoccupation with personal growth (Judge et al., 2006; Miller & Campbell, 2008). A well-known example is Steve Jobs; he was recognized for his narcissism but managed to revolutionize multiple industries, drive the creation of new ones, and lead to radical, disruptive innovations (Chatterjee & Hambrick, 2007). Narcissistic CEOs are known to shift risk assessments (Campbell et al., 2004), thus interpreting riskier prospects as opportunities for considerable payoff (Gerstner et al., 2013).

Narcissistic entrepreneurs strongly desire recognition and are likely to take bold actions that support creativity and innovation (Paulhus & Williams, 2002). Narcissism is associated with self-enhancement; therefore, in the context of G-AI, its use might help individuals high in narcissism to exert (new) power over people and machines. At low to moderate levels, narcissistic entrepreneurs would be able to regulate such tendencies while using G-AI and can use their charismatic personas to rein in underlying potential tendencies. However, we expect narcissism to have a tipping point where its negative aspects become predominant. Highly narcissistic entrepreneurs may impulsively pursue questionable opportunities, leading to the misuse of resources and premature abandonment of viable projects (Brownell et al., 2023). At high levels of narcissism, entrepreneurs should exhibit low self-control, antisocial behavior, and arrogance (Foster & Trimm, 2008), increasing the likelihood of unethical conduct actions (Amernic & Craig, 2010). Highly narcissistic entrepreneurs typically set unrealistic goals for themselves, and the desire for self-affirmation can drive them to carry out unethical (sometimes creative) behaviors to achieve them (Duchon & Drake, 2009). This drive for self-affirmation can result in unethical creativity, as suggested by studies linking narcissism with fraudulent behavior (Rijsenbilt & Commandeur, 2013). As narcissistic tendencies intensify, the ability to self-regulate diminishes, heralding increasingly destructive and self-serving behaviors (Paulhus & Williams, 2002), which we expect will extend to the use of G-AI, heightening the risk of unethical creativity. Therefore:

H5: The relationship between G-AI usage and unethical creativity is moderated by narcissism, such that the relationship between G-AI usage and unethical creativity will be strongest for entrepreneurs who exhibit high levels of narcissism.

Research methods

Research context

The sample comprises technology entrepreneurs from Bangladesh and India, chosen for their adoption of G-AI. Both nations have established themselves as competitive participants in global technology entrepreneurship (Hossain & Al Asheq, 2019; Satyanarayana et al., 2022; Verma & Singh, 2022). Indian tech entrepreneurship has surged recently, with start-ups reaching 84,012 in 2022 as evident in (The Economic Survey, 2022-23 2023). Similarly, Bangladesh has seen a substantial growth in this sector, with tech start-ups increasing from fewer than 200 in 2015 to over 2,500 in 2023 (Bangladesh Startup Investment Report, 2022). This growth is facilitated by transformative technological advances in entrepreneurial venturing.

While India and Bangladesh have experienced significant growth in technology entrepreneurship, there have been instances of unethical conduct and controversies. For instance, in 2014, Flipkart faced backlash over its "Big Billion Day" sale. It was accused of artificially inflating prices before the sale and then giving discounts on the inflated prices, misleading customers (Punit, 2015). Such unethical practices eroded customer trust in India's e-commerce sector, resulting in significant reputational damage to Flipkart. Another example, Ola, an Indian ride-hailing service, was accused of operating unlicensed taxis in Delhi, leading to a temporary ban on its operations due to a disregard for public safety and the rule of law (Shakil, 2016). The controversy damaged customer confidence in ride-hailing platforms, raised concerns about rider safety, and pushed local authorities to enforce stricter licensing requirements. A similar incident occurred in Bangladesh, where the ride-hailing service Pathao faced controversy, being accused of compromising user privacy by accessing unnecessary data and personal information from users' smartphones (Khan, 2019). Ethical controversies undermine consumer confidence in local digital platforms, accelerate calls for robust data protection legislation, and, in the long run, encourage other start-ups to adopt stronger data governance policies to maintain user trust. This also underscored that the

entrepreneurial ecosystem needs to balance innovation with the ethical deployment of technology. These controversies highlight that both countries are innovation hubs with thriving entrepreneurial ecosystems, yet they are also characterized by heightened ethical risks. Therefore, Bangladesh and India provide appropriate research sites to study entrepreneurs' use of G-AI and its effects on their creative behavior.

Sample and data collection

We implemented a time-lagged survey to collect data from Bangladesh and India. Our samples were selected from two databases: Bangladesh Association of Software and Information Services, BASIS (2022), for Bangladesh and Techcircle (2022) for India. These databases are chosen because both platforms serve as comprehensive repositories of technology-driven entrepreneurial firms in their respective countries. BASIS is Bangladesh's leading national trade body for the software and IT-enabled services industry, representing over 2000 registered firms. In addition, Techcircle is an established Indian technology and startup intelligence platform that curates verified data on high-growth entrepreneurial firms, including funding rounds, founders, and sectoral specializations (Techcircle, 2022).

We use random sampling to minimize systematic bias and enhance the external validity of the findings (Short et al., 2002), enabling the study to generalize its results across the diverse entrepreneurial populations in India and Bangladesh. Random sampling also reduces systematic error, allowing for more accurate parameter estimates and improving the reliability of hypothesis testing. Moreover, it strengthens the statistical power of inferential analyses by ensuring that sample characteristics are not skewed by researcher preferences or network biases.

The databases contained approximately 2,021 and 10,103 firms, respectively, at the time of the data collection. To ensure adequate statistical power and external validity, we calculated the minimum sample size using Cochran's (1942) formula with a 95% confidence level, $\pm 7\%$ margin of error, and maximum variability (p = 0.50). For Bangladesh, the required minimum sample was 179; for India, the required minimum was 192. In the first data collection phase (t1), we emailed the questionnaire (in English) using Qualtrics to the founders/entrepreneurs of 2,000 firms each in India and Bangladesh. We accumulated email addresses from these databases, company websites, and LinkedIn. At t1, we collected data on G-AI usage. We asked the entrepreneurs about the use of various G-AI platforms and tools (e.g., ChatGPT, Gemini, Claude, Dall-E, Midjourney, etc.) to capture the frequency, infusion, and routinization of G-AI use. We also took this opportunity to confirm the entrepreneurial status of these firms by posing two questions based on Shir et al. (2019): 'Has the firm introduced any new products to the market in the past three years?' and 'Has the firm identified and capitalized on any new or unique opportunities in the past three years?'.

Our initial outreach yielded responses from 199 firms in Bangladesh and 213 in India. Three Bangladeshi and eight Indian responses were excluded for failing to meet the criteria of entrepreneurship status. Four weeks later, during the second phase of data collection (t2), we contacted the founders and entrepreneurs again and asked them to introduce us to someone on the management team with whom they had a close working relationship to provide us with information about them. We requested data on Machiavellianism, psychopathy, narcissism, and seeking information on creativity and unethical creativity. We provided written assurance to the respondents (e.g., directors, general managers, deputy general managers) that the entrepreneurs would not have any access to their responses, in accordance with the guidelines of Mai et al. (2022). We followed this approach because entrepreneurs self-reporting their own creativity and unethical creativity, as well as their own personality traits, may compromise the validity of the data and exacerbate the risk of social desirability bias (Fisher & Katz, 2000). Our final sample comprised 188 firms from Bangladesh and 201 from India, all of which participated at both data collection points. The response rate was 9.4% in Bangladesh and 9.8% in India, which is consistent in the Indian (Gopal & Thakkar, 2016; Saxena & Sahay, 2000) and Bangladeshi (Mostafiz et al., 2025) contexts. Since we collected survey data from two countries, we conducted an assessment of measurement invariance. This is reported in the Online Supplementary Table 1.

Measurement

Unless otherwise stated, all multi-item constructs were measured on a seven-point Likert scale with anchors ranging from 1 = strongly disagree/very few to 7 = strongly agree/very much. Details of the measures are presented in Appendix I in the online supplementary material. We measured *G-AI usage* with nine items adopted from Sundaram et al. (2007). The first two items capture the frequency of G-AI use, three items capture its routinization, and three items demonstrate its infusion into work. The DPTs are measured by operationalizing *Machiavellianism* (4 items), *psychopathy* (4 items), and *narcissism* (4 items) with items from Brownell et al. (2023) and Jonason and Webster (2010). We measured *unethical creativity* with six items adapted from Mai et al. (2022). For the baseline hypotheses, we measured *creativity* using nine items adopted from Tierney et al. (1999), frequently used in entrepreneurship studies (Khedhaouria et al., 2015; Nisula & Olander, 2023).

Several control variables were included in the analysis to minimize alternative explanations of the hypothesized

relationships. First, studies indicate a positive correlation between an *entrepreneur's age* and outcomes (Rose et al., 2006). Concurrently, it has been suggested that the influence of DPTs tends to diminish as one ages (Barlett & Barlett, 2015). Second, *gender* can determine key entrepreneurial outcomes (Jennings & Brush, 2013), with men typically exhibiting higher scores than their female counterparts on all three DPTs (Jonason & Davis, 2018). Third, *prior entrepreneurial experience* is associated with creativity (Zhan et al., 2022) and is included as a control variable. Fourth, *education* has been found to positively correlate with entrepreneurial activity and creativity (Tantawy et al., 2021). Fifth, we also control for the *country* dummy (Bangladesh = 0 and India = 1). Sixth, *marital status* can mask the impact of an additional income source through creativity (Kang et al., 2021) and stimulate unethical behavior (Liu, 2008). Lastly, *initial capital* has been controlled as it may explain a firm's ability to adopt new technologies (Wang, 2022).

Assessment of potential biases

We performed a non-response bias test using ANOVA to detect differences between respondents and non-respondents, assuming that late respondents are more similar to non-respondents than early respondents (Sieger et al., 2013). Following Armstrong and Overton (1977), we contrasted the first 7% of the dataset with the last 7%, treating the latter as equivalent to non-responses. Our analysis did not reveal significant differences between the variables, reducing concern over non-response bias. Second, the dataset used in this study was gathered at two distinct time points. This approach counters the preliminary risk of simultaneity bias (Guide & Ketokivi, 2015). Third, we adopted several steps to reduce the potential impact of common method variance (CMV). Guided by Chang et al. (2010), we integrated redundant questions into both surveys that were not used in this study and removed any psychological barriers that could allow respondents to discern the study's constructs. To examine CMV, we conducted Harman's single-factor analysis via principal component analysis with varimax rotation (Hair et al., 2010). The first component explained less than 50% of the variance, accounting for only 23.79%. We also conducted a more rigorous single latent factor analysis. The results ($x^2 = 1239.8472$, df = 148, CMIN/df = 8.377, RMSEA = 0.478, CFI = 0.184) differed markedly from the six-factor confirmatory factor model ($x^2 = 421.397$, df = 238, CMIN/df = 1.77, RMSEA = 0.049, CFI = 0.901). Therefore, we conclude that any possible CMV has minimal influence in this research (Podsakoff et al., 2003). We also conducted rigorous examinations of endogeneity bias and sample selection bias, which are reported in the online supplementary material.

Analyses and Results

Descriptive statistics, reliability, and validity

The firms in our sample range from three to eight years old and employ between 14 and 63 staff. These tech firms provide diverse services, including software solutions, business process outsourcing, online news portals, e-healthcare, legal and administrative services, digital marketing, e-sports, web design, digital agricultural services, data stream and mining, and augmented reality design services.[1]

Table 1 presents the results of correlation analyses, normality tests, reliability assessments, validity checks, and multicollinearity tests. Correlation results suggest that G-AI usage is positively associated with creativity and unethical creativity, and that DTPs are interrelated as well. The values of Skewness and Kurtosis are within the ± 2 cut-off point, suggesting a normal distribution of the data (Shapiro & Wilk, 1965). Both the Cronbach Alpha and composite reliability scores of the constructs exceed 0.7, indicating internal consistency (Hair et al., 2010). Convergent validity is supported as all average variance extracted (AVE) values surpass 0.50 (Fornell & Larcker, 1981), indicating that more than 50% of the variance in the indicators is captured by their respective latent constructs. Discriminant validity is also established as the square roots of AVE values (shown on the diagonal in Table 1) are greater than the corresponding inter-construct correlations, and all AVE values exceed the maximum shared variance (MSV), demonstrating adequate construct distinctiveness (Cable & DeRue, 2002). Lastly, multicollinearity diagnostics show that variance inflation factor (VIF) values range from 1.253 to 2.461, well below the recommended threshold of 5 (Graham, 2003).

Results of hypothesized relationships

We used regression analysis to examine the conceptual model using the pooled dataset. Tables 2 and 3 report the results. The results of unpooled data are available in the online supplementary material. Model 1 in all regression analyses includes only the control variables. Model 2 in Table 2 shows that G-AI usage has no significant effect on creativity ($\beta = 0.029$, p > 0.05, t = 0.72); therefore, H1 is not supported. However, Model 2 in Table 3 reports the significant effect of G-AI usage on unethical creativity ($\beta = 0.218**$, p < 0.05, t = 2.38), supporting H2.

For moderation, first, we conduct the intersect moderation to examine the effects of Machiavellianism, psychopathy, and narcissism on the relationship between G-AI usage and

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[1] Table 11 in the online supplementary material presents the sample characteristics.

Table 1 Correlations, reliability, and validity (pooled, n=389)

Constructs	1	2	3	4	5	6
1. G-AI use	0.720					
2. Creativity	0.205**	0.711				
3. Unethical creativity	0.238**	-0.204**	0.741			
4. Machiavellianism	0.214**	0.190*	0.293**	0.727		
5. Psychopathy	0.164**	0.168**	0.116**	0.167**	0.715	
6. Narcissism	0.242**	0.239**	0.271**	0.272**	0.282**	0.733
Control variables						
Initial capital	0.115	0.073	0.104	0.053	0.012	0.019
Prior entrepreneurial experience	0.050	0.102	0.024	0.028	0.108	0.045
Entrepreneur age	0.014	0.049	0.054	0.044	0.073	0.059
Gender	0.039	0.027	0.010	0.048	0.064	0.059
Entrepreneur's education	0.044	0.095	0.026	0.087	0.006	0.031
Professional qualification	0.024	0.027	0.005	0.065	0.039	0.071
Country	0.011	0.008	0.016	0.004	0.020	0.017
Marital status	0.003	0.054	0.017	0.075	0.091	0.053
Mean (construct)	56.017	52.341	36.439	22.189	23.782	21.861
Standard deviation	3.332	4.280	2.121	2.919	2.035	2.442
Cronbach Alpha	0.761	0.838	0.742	0.722	0.751	0.779
Skewness	0.715	0.612	0.602	0.858	0.953	0.857
Kurtosis	1.783	0.984	1.708	0.977	0.740	1.330
Composite reliability	0.744	0.741	0.713	0.765	0.758	0.780
AVE	0.518	0.506	0.549	0.528	0.511	0.538
MSV	0.347	0.296	0.251	0.311	0.341	0.358
VIF	2.133	2.121	1.430	2.461	1.253	1.288

Diagonal values are the square root of AVE values

*p < 0.05, **p < 0.01

Table 2 Results of regression analysis of creativity (pooled, n=389)

Variables	Model 1	Model 2
Control variables		
Entrepreneur age	0.013	0.019
Gender	0.019	0.010
Entrepreneur's education	0.007	0.017
Professional qualification	0.018**	0.018
Country	0.008	0.012
Marital status	0.011	0.019
Initial capital	0.022	0.017
Prior entrepreneurial experience	0.018**	0.015**
Explaining variables		
G-AI usage		0.029
Intercept	3.424	2.754
R2	0.111	0.142
ΔR2		0.016
F-ratio	1.020	2.597**
Likelihood-ratio test (*p*)		0.012
Bayesian criterion (BIC)		1757.813

**p < 0.05

unethical creativity. Models 3, 4, and 5 in Table 3 show the results. The findings suggest that Machiavellianism and narcissism positively moderate the relationship between G-AI usage and unethical creativity (β = 0.025**, p < 0.05, t = 2.31; β = 0.027**, p < 0.05, t = 2.48, respectively); however, the moderating effect of psychopathy is non-significant (β = 0.003, p > 0.05, t = 0.33). Second, we attempt to understand the relationship between G-AI usage and unethical creativity at low versus high DPTs. We computed this analysis based on the median value of Machiavellianism, narcissism, and psychopathy. The results in Table 4 show that at high levels of Machiavellianism and narcissism, the relationship between G-AI usage and unethical creativity is significant; however, the relationship between G-AI usage and unethical creativity is non-significant at low and high levels of psychopathy. We also performed the *chi²* difference test between groups, and the differences are higher than 3.84 (95% confidence level, given one *df*), indicating statistical significance. Hence, H3 and H5 are supported, and H4 is not supported. We also conducted rigorous robustness checks. These additional analyses are available in the online supplementary material.

Table 3 Results of regression analysis of unethical creativity (pooled, n = 389)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
Entrepreneur age	0.016	0.012	0.017	0.021	0.046	0.011
Gender	0.008	0.018**	0.001	0.021	0.014	0.017
Entrepreneur's education	0.020**	0.017**	0.086	0.010	0.051	0.013
Professional qualification	0.016	0.018	0.071	0.062	0.040	0.016
Country	0.016	0.009	0.009	0.010	0.010	0.013
Marital status	0.006	0.008	0.017	0.020	0.014	0.006
Initial capital	0.001	0.002	0.012	0.082	0.066	0.001
Prior entrepreneurial experience	0.022**	0.006	0.041	0.065	0.009	0.009
Explaining variables						
G-AI usage		0.218**	0.203**	0.206**	0.202**	0.183**
Machiavellianism			0.127**			0.113**
G-AI usage * Machiavellianism			0.025**			0.020**
Psychopathy				0.019		0.009
G-AI usage * Psychopathy				0.003		0.001
Narcissism					0.136**	0.118**
G-AI usage * Narcissism					0.027**	0.021**
Intercept	3.577	2.572	1.956	2.175	2.019	1.927
R2	0.126	0.132	0.146	0.133	0.141	0.128
ΔR2	0.015	0.010	0.014	0.013	0.009	0.013
F-ratio	1.125	2.816**	2.694**	2.401**	2.125**	3.183**
Likelihood-ratio test (*p*)		0.016	0.011	0.012	0.011	0.024
Bayesian criterion (BIC)		1939.216	1946.735	1945.437	1937.685	1942.293

**p < 0.05

Discussion

We theorized about the outcomes of G-AI usage, anticipating that it may positively lead to creativity but at the same time fuel unethical creativity, conditioned by DPTs. Our theoretical reasoning began with a generally held assumption that G-AI usage positively affects creativity (our baseline hypothesis). Our findings suggest that this taken-for-granted assumption, despite scholarly reluctance regarding the linkage between G-AI and creativity (Amabile, 2020), may be wrong. Contrary to our baseline hypothesis, we found no significant direct effect of G-AI usage on creativity. This finding contradicts the common assumption that generative technologies inherently enhance creative outcomes (Haefner et al., 2021; Townsend & Hunt, 2019). One plausible explanation for this contradiction to our baseline hypothesis is that not all entrepreneurs consider G-AI as a creativity-enhancing tool (Glikson & Woolley, 2020). When individuals fail to perceive the value of AI for creative endeavor, its use can decline. For example, recent HR and organizational psychology studies further emphasize the importance of training users to develop a sense of creative agency when interacting with AI, conditions under which AI co-created creativity is more likely to flourish (Bastida et al., 2025). Thus, prior research shows that perceptions of AI influence how

individuals use it (Glikson & Woolley, 2020). If entrepreneurs primarily use G-AI for drafting, analysis, or routine support tasks, its creative potential may not be fully activated. In such cases, differences in G-AI usage may reflect how frequently the tool is used rather than how creatively it is applied.

Second, because G-AI systems rely on patterns learned from existing data (Raisch & Fomina, 2025), they are particularly effective at recombining and extending existing ideas. However, recombination does not automatically translate into higher-quality creativity. An increase in idea quantity or variation does not guarantee greater originality or usefulness (Runco & Acar, 2012; Townsend & Hunt, 2019). Our findings suggest that efficiency gains should not be confused with creativity gains. While G-AI may increase the speed and efficiency of entrepreneurial decision-making (Liu & Wang, 2024), greater efficiency does not automatically result in greater novelty (Amabile, 2020). Supporting faster idea development or refinement does not necessarily produce more original outcomes. In this sense, G-AI may primarily function as a productivity-enhancing tool rather than a driver of fundamentally new ideas.

Third, a ceiling-effect explanation is plausible. It is possible that many entrepreneurs already operate at relatively high levels of creativity due to their experience and

Table 4 Results of regression analysis between G-AI and unethical creativity (low versus high DPTs, pooled, n = 389)

	Outcome variable: unethical creativity			
	Low level of Machiavellianism		High level of Machiavellianism	
	Coefficient	p-value	Coefficient	*p*-value
G-AI Usage	0.038	0.081	0.169**	0.012
	Low level of psychopathy		High level of psychopathy	
	Coefficient	p-value	Coefficient	*p*-value
G-AI Usage	0.011	0.775	0.026	0.176
	Low level of narcissism		High level of narcissism	
	Coefficient	p-value	Coefficient	*p*-value
G-AI Usage	0.042	0.099	0.171**	0.031

**p < 0.05

established innovation practices (Nisula & Olander, 2023). When creativity is already part of how entrepreneurs think and work, the additional contribution of G-AI may be limited. Under these conditions, G-AI may complement existing creative processes rather than fundamentally transform them. Prior research suggests that in contexts characterized by causal ambiguity, individuals tend to attribute favorable outcomes to their own abilities, particularly when authorship is difficult to disentangle (Breugst & Shepherd, 2017; Mandl et al., 2016). However, the absence of a direct effect suggests that this mechanism may operate differently than anticipated. While entrepreneurs may attribute successful idea development primarily to their own abilities, such internal attributions may reinforce their existing creative identity rather than substantially altering their broader self-perceived creativity (Krueger, 2007; Theoharakis et al., 2021). In other words, G-AI usage may support creative episodes without necessarily shifting how entrepreneurs view their creativity overall. This distinction helps reconcile our theoretical expectations with the empirical findings. These perspectives offer a more complex understanding of G-AI's creative potential, highlighting that perceptions of the tool may influence creative outcomes. These plausible explanations suggest that the relationship between G-AI usage and creativity is more conditional than often assumed.

The absence of a direct effect on general creativity does not preclude effects on unethical creativity. The mechanisms underlying unethical idea generation—particularly strategic manipulation and moral disengagement—differ from those driving constructive creativity. Drawing on attribution theory, we hypothesize that G-AI usage can lead to unethical creativity, as entrepreneurs might be encouraged to disengage from their moral beliefs that normally prevent unethical behavior. This may occur because their involvement activates attribution distancing and moral disengagement

because of the G-AI system, allowing them to justify their actions and shift the blame to the system. The validation of the association between G-AI usage and unethical creativity corroborates previous research indicating that G-AI is used unethically despite an abundance of ethical guidelines (Strümke et al., 2022).

Self-regulation, however, puts the spotlight on DPTs and individuals' (in)ability to self-regulate (due to the magnitude of those DPT traits) as the theoretical basis for why unethical creativity occurs from G-AI usage. Our robustness tests reveal that G-AI usage positively affects firm performance. The appeal of improved performance can lead to overemphasizing the pursuit of benefits, even when crossing ethical boundaries. While we show that G-AI usage by entrepreneurs is an enabler of deviant behavior and provides an opportunity to pursue self-serving behaviors, the willingness and ability to use G-AI egregiously for unethical creativity are amplified by the magnitude of DPTs present in an individual, a thesis substantiated by the moderating effects found in our study. This supports concerns about the inadequate integration of ethical values in G-AI systems (Abdelhalim et al., 2024) insofar as they present opportunities for unethical creativity.

The dramatic growth of G-AI demonstrates how entrepreneurial decisions have become increasingly technologically influenced (Verbeek, 2014). This is problematic for entrepreneurs who tend to disengage from their actions morally (Qin et al., 2020, 2022; Shepherd et al., 2013). Underpinned by the principles of self-regulation, our findings enrich the argument made by Brownell et al. (2023) that, at low to moderate levels of the DPTs, entrepreneurs may be better able to regulate their predispositions toward unethical behavior. We anticipated that if the boundary conditions of higher levels of Machiavellianism (H3), psychopathy (H4), and narcissism (H5) are met, the association between G-AI

and unethical creativity would strengthen markedly. Our findings support the idea that high levels of Machiavellianism and narcissism traits deplete an entrepreneur's cognitive ability to self-regulate impulses and behaviors, leading to marked increases in unethical creativity when using G-AI. However, unexpectedly and worryingly, even at moderate to high levels of these traits, entrepreneurs struggle to regulate their harmful impulses and eventually fail to self-regulate, leading to more unethical creativity from G-AI usage. Therefore, while empirical research predicts that narcissism and Machiavellianism are associated with ethically questionable behaviors (Amernic & Craig, 2010; Cesinger et al., 2023; Jones & Paulhus, 2009; Myung & Choi, 2017; Rijsenbilt & Commandeur, 2013), our study contributes a psychologically grounded self-regulation thesis for why human behavior occurs in the form of unethical creativity when it is technology-influenced.

Contrary to expectations, our findings did not reveal any moderating effect from psychopathy (neither at moderate nor peak levels). This finding aligns with the argument that the psychopathy trait does not fit well with the creative stereotype (Elsbach & Kramer, 2003). An association between psychopathy and creativity is ambiguous (Lebuda et al., 2021; Sordia et al., 2022). These findings are encouraging because they support the growing realization that DPTs are not all inherently harmful, destructive, or dysfunctional (Brownell et al., 2023; Cesinger et al., 2023). Two possible explanations for this exist. First, psychopathy is invariably maladaptive (Smith & Lilienfeld, 2013), while innovation-centered activities demand adaptability skills (Smith & Webster, 2018). Second, the need for immediate gratification and impulsivity for psychopaths is less likely to be associated with liking a technology that would bring power over others in the long run rather than immediately. In turn, our empirical findings introduce self-regulation to correctly anticipate which DPTs are situationally or contextually relevant to specific behavioral outcomes.

Implications for theory

We theorized that the trinity of DPTs can inadvertently stimulate unethical creativity by blurring ethical boundaries amid G-AI's attributional displacement and moral distancing power. Even though an individual possesses a dark trait, it does not necessarily mean that the individual would commit negative actions (DeNisi, 2015). The level and type of DPTs an entrepreneur possesses determine whether they increase the likelihood of unethical behavior. In a G-AI-driven entrepreneurial setting, individuals with high levels of narcissism might exploit G-AI tools to reinforce their grandiose self-image; highly Machiavellian individuals could deploy G-AI for subtle strategic manipulation of others. Thus, we enrich

theory suggesting that DPTs are contextual (Cesinger et al., 2023; Lebuda et al., 2021).

Our study offers novel contributions by introducing attribution theory and self-regulation into the domain of entrepreneurial G-AI usage (Bankins & Formosa, 2023). While prior research has explored AI's affordances or risks separately (Glikson & Woolley, 2020; Strümke et al., 2022), we integrate these literatures to theorize how attributional reorientation, moral distancing, and DPTs interact to generate and amplify unethical creativity from entrepreneurs' G-AI use. We move beyond surface-level ethical concerns and explain *why* entrepreneurs may reorient morally ambiguous AI outputs in self-serving ways, depending on their personality traits. This layered framework clarifies how G-AI creates space for human agency, cognitive bias, and moral disengagement to converge. We advance theory by shifting attention from the functional capacities of G-AI to its psychological implications for entrepreneurial agency and ethics. G-AI creates attributional ambiguity (Zeiser, 2024), which may prompt entrepreneurs to use G-AI to deflect ethical responsibility onto it (Köbis et al., 2025). This nuance departs from prior AI ethics research that focuses on either technological transparency or organizational safeguards (Abdelhalim et al., 2024). By linking attribution theory to DPTs, we highlight how individual psychological traits moderate the deployment of G-AI-generated content, thereby correcting for the underrepresentation of this perspective in both the entrepreneurship and AI literatures (Brownell et al., 2023; Hmieleski & Lerner, 2016).

Our work differentiates itself from prior studies treating attribution processes as universal (Mandl et al., 2016; Mantere et al., 2013; Pardo & Alfonso, 2017). We introduce individual differences as an explanatory factor: DPTs may constrain or enhance certain attributional biases in human–AI interaction. We systematically examine how DPTs function in the novel context of G-AI collaboration. We explain why some users might be more likely to misuse AI or avoid accountability, driven by narcissistic entitlement or Machiavellian rationalization. By integrating dark personality traits as a moderating mechanism in the relationship between G-AI usage and unethical creativity, our study advances attribution theory and illuminates when and for whom the classic biases (e.g., self-serving credit, scapegoating blame, moral disengagement) are most pronounced in the age of AI (Köbis et al., 2025). This contributes to theory by reconceptualizing attribution theory to include personality-driven differences and by identifying high-risk profiles who may use AI, externalize blame, or fail to credit AI appropriately in collaborative settings. Below, we provide illustrative explanations of our contributions.

Scholars suggest that the human–G-AI symbiotic relationship may more often enable and encourage individuals to conduct questionable actions and to find loopholes

to circumvent rules and regulations (Puntoni et al., 2021). The question unanswered among such speculation is whether the fault lies in the G-AI, the human, or a combination of the two, and what contingencies suppress or escalate technology-influenced unethical behavior. Our study attempts a cohesive examination of G-AI use and its potential to foster creativity and unethical creativity. Attribution theory, which centers on how individuals assign causes to their successes and failures, offers a valuable lens for interpreting our findings. First, the lack of influence of G-AI usage on creativity challenges the common assumption that technology inherently fosters conventional creative processes. While G-AI can provide tools and capabilities, creativity might still primarily hinge on human factors such as imagination, insight, and the ability to make non-obvious connections, which G-AI might not directly enhance. We argue that entrepreneurs might attribute success more to themselves than to technological tools because creativity is a multifaceted construct primarily driven by individual traits and cognitive abilities (Townsend & Hunt, 2019) rather than solely by technology. Conversely, the influence of G-AI usage on unethical creativity offers a stark counterpoint. Under attribution theory, entrepreneurs appear more inclined to attribute unethical conduct to G-AI's capabilities, possibly absolving themselves of some moral responsibilities. Our contribution advances the concerns raised by Martin and Freeman (2004) that technological integration brings critical ethical dilemmas to the fore, including issues of responsibility, privacy, and the potential for misuse of information. A propensity for firms to credit G-AI with enhancing performance metrics underscores the perceived value of technological investment. This attribution, however, must be balanced with ethical vigilance (Kaplan & Haenlein, 2019) and caution against the potential misuse of G-AI.

We heed the call of Amabile (2020, p.352), who argues that "organizational researchers of creativity and innovation are missing the boat if they do not invest significant energy in studying G-AI and computer-assisted human intelligence, the ways in which they might yield creative breakthroughs." Thus, second, we intersect the study of the double-edged sword of G-AI usage by entrepreneurs with an inquiry into personality traits in entrepreneurship (Klotz & Neubaum, 2016). Considering G-AI's multifaceted benefits, entrepreneurs with higher DPTs are more likely to exploit G-AI-enabled technologies to ascertain often malevolent desires. This line of reasoning is rooted in the self-regulation of DPTs. For example, according to Paulhus and Williams (2002, p.100), "individuals with these traits share a tendency to be callous, selfish, and malevolent in their interpersonal dealings." Consequently, a stream of research condemns these traits as associated with adverse outcomes (Creek, 2018; Liu et al., 2019), despite some value-adding effects (e.g., Lebuda et al., 2021; Resick et al., 2009; Smith & Webster,

2018). These findings raise the concern that being in control of G-AI represents a new form of power, a new managerial tool that can be used for either benefit or deviance. As the magnitudes of narcissist and Machiavellian traits rise, cognitive resources needed to self-regulate deviant impulses when presented with technology-driven opportunities to behave immorally diminish rapidly, vastly exacerbating the effect of G-AI usage on unethical creativity. Therefore, our second contribution to the self-regulation of entrepreneurs is a predictive apparatus and empirical evidence on narcissism and Machiavellianism as boundary conditions for G-AI-enabled unethical behavior. In conjunction with our first contribution on the impact of G-AI on unethical creativity, these advancements provide the scaffolding for a self-regulation theory of deviant behavior resulting from G-AI-human interaction.

Finally, given the paucity of theoretical knowledge about G-AI's application in entrepreneurship (Chalmers et al., 2021; Obschonka & Audretsch, 2020), our research contributes to the evolving dialogue at this intersection (Chalmers et al., 2021; Townsend & Hunt, 2019). G-AI's unethical use is a function of the opportunities the technology presents to offload responsibility, thereby curtailing the energy devoted to self-regulation, and of the personality traits of the human actor using the G-AI. Thus, while academic interest in the various entrepreneurial behaviors and outcomes of DPTs has accelerated over the last decade (Brownell et al., 2021), research on trait-based antecedents of creativity has only recently begun to incorporate personality traits of entrepreneurs as a predictor (Smith & Webster, 2018). The current debate must pivot around how much G-AI's impact will be positive or negative, for whom, in what ways, and how quickly.

Implications for practice

While G-AI has the potential to serve as a powerful catalyst for innovation and productivity, we show it can be exploited for unethical behavior, especially by individuals exhibiting high levels of Machiavellianism and narcissism. Close monitoring is required, and the ethical use of G-AI-based technologies should be nurtured. G-AI can generate unethical creativity, and failing to account for DPTs can result in unethical behaviors detrimental to reputation and potentially subject to litigation. An entrepreneur with pronounced Machiavellianism and narcissism could misuse this technology to manipulate the data for personal gains, potentially at the cost of stakeholders. Therefore, self-regulation requires resourcing and nurturing. From a policy perspective, our findings suggest robust regulations on G-AI adaptation. Policymakers must strike a careful balance that fosters innovation and growth without enabling harmful behaviors. Developing comprehensive, adaptable regulations that reflect the multifaceted nature of G-AI and its users is essential.

Limitations and future research

Our study is not without limitations, but these offer fruitful avenues for future research. First, our research design, largely cross-sectional, limits the potential for exploring temporal dynamics. A longitudinal approach is required to capture the evolution of G-AI use and its interaction with personality traits. Second, the data used in this study are from Bangladesh and India. Both countries suffer high levels of corruption. We were unable to capture cultural sensitivity, which may influence the presence or prominence of DPTs. Future research could consider context sensitivity and evaluate a broader range of personality constructs to further understand G-AI use and its implications for (un) ethical creativity. Third, G-AI use and its ethical implications transcend individual entrepreneurs and require further study. While this study focused on individual-level traits, future research could extend this framework by incorporating organizational and institutional-level factors, such as ethical culture, regulatory enforcement, or environmental dynamism, that may buffer or amplify the influence of dark traits in AI-augmented entrepreneurial contexts. Continued research in this area is necessary and holds great potential for informing our understanding of the future of G-AI in ethics and entrepreneurship.

Declarations

Conflict of interest There is no conflict of interest that influences the work.

Informed consent We confirmed all informed consent was obtained from all participant before the data collection commenced.

Research involving human participants and/or animals The data in this is based on survey conducted in the India and Bangladesh. Before the data collection, ethical approval has been obtained following strict data privacy and security measures in compliance with privacy laws and ethical guidelines in the UK. We adheres to the General Data Protection Regulation (GDPR) (EU/UK) and the UK Data Protection Act 2018. Data is controlled and managed by the University of Leicester. Participants received informed consent forms clearly explaining the study's objectives, data usage policies, and their right to withdraw at any time. For confidentiality, the research team employed anonymization, pseudonymization, encryption, and restricted access protocols, safeguarding against unauthorized access and mitigating data security risks.

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