Unveiling the Influence of Personality, Identity, and Organizational Culture on Generative AI Adoption in the Workplace

Research Paper

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Abstract. Artificial intelligence (AI) significantly impacts workplace dynamics and employee behavior. However, limited research examines how personality traits, identity, and organizational culture influence employee engagement with generative AI (GenAI). This qualitative study used 23 expert interviews to explore these effects. Analysis revealed four aggregated dimensions: (1) Personality-Driven AI Usage Behavior; (2) AI-Driven Identity Change; (3) Organizational and Cultural AI Adoption Factors; and (4) Organizational Risks of AI Use. Additionally, four AI identity archetypes were identified: Innovative Pioneers, Hidden Users, Transparent Users, and Critical Skeptics, reflect how individuals incorporate GenAI into their identity and usage behavior. The findings suggest organizations should foster transparent AI integration through supportive cultures, ethical guidelines, and targeted training.

Keywords: *Generative AI, Personality Traits, AI Identity, Organizational Culture, AI Adoption*

1 Introduction

In an era characterized by rapid digital transformation, artificial intelligence (AI) technologies are increasingly shaping workplace dynamics and employee behavior, with 86% of organizations expecting AI and information processing technologies to fundamentally transform their businesses by 2030 (World Economic Forum 2025). Organizations adopting AI driven tools such as generative AI (GenAI), that is, technologies capable of producing novel and realistic content based on user prompts (Banh and Strobel 2023), encounter diverse employee responses (Kellogg et al. 2020) to the integration of these technologies into their workflows (Cremer and Kasparov 2021), ranging from proactive adoption and transparent integration to strategic concealment and ethical dilemmas (Dhirani et al. 2023). This variation can be partially explained by individual differences in personality traits, identity formation processes, and broader organizational and cultural contexts. Prior research highlights the critical role personality traits, both positive, represented by the Big Five, and negative, captured in the Dark Triad, play in influencing attitudes and behaviors towards technology adoption (Devaraj et al. 2008; Paulhus and Williams 2002). Similarly, identity theory provides a valuable theoretical lens through which we can understand how personal and professional identities evolve (Carter and Grover 2015; Carter et al. 2020) as employees increasingly interact with advanced AI tools, thereby forming new identities specifically centered around AI (Cao et al. 2023; Richter and Schaller 2025). However, personality traits and identity alone do not fully capture the complexity of AI adoption behaviors. Organizational and cultural dimensions, ranging from internal organizational structures and values to external societal attitudes and competitive pressures (Chesbrough 2010; Schein 2010), significantly influence how openly or covertly individuals engage with AI technologies. Therefore, this study aims to explore how personality traits, AI identity, and organizational and cultural influences shape AI adoption and usage behaviors in the workplace.

2 Theoretical background

2.1 Personality Traits and AI Usage

Personality traits significantly influence individual behavior, especially in organizational contexts where technology adoption is crucial (Devaraj et al. 2008; Schepman and Rodway 2023). Psychological research distinguishes between positive traits, commonly conceptualized in the Big Five framework, including openness, conscientiousness, extraversion, agreeableness, and neuroticism (McCrae and Costa 1997), and negative traits, encompassed by the Dark Triad, including narcissism, Machiavellianism, and psychopathy (Paulhus and Williams 2002). Positive personality traits like openness and conscientiousness facilitate ethical behavior, innovation, and a responsible approach toward technology use (McCrae and Costa 1997). Individuals high in openness tend to embrace new technological solutions (McElroy et al. 2007), using them to foster creativity and effective problem-solving. Conscientious employees typically approach technology adoption methodically and responsibly (Lee and See 2004), integrating AI into their workflows with a focus on reliability and integrity. Conversely, Dark Triad traits, including narcissism, Machiavellianism, and psychopathy, often predict more manipulative, self-serving behaviors (LeBreton et al. 2018), such as the strategic concealment or unethical use of AI technologies. Narcissistic individuals may exploit AI to enhance their perceived competence or status, whereas Machiavellian individuals might strategically conceal their AI use to maintain control or gain competitive advantages.

2.2 IT identity theory and AI Identity

The IT identity Theory, introduced by Carter and Grover (2015, p. 938), defines IT identity as “the extent to which a person views use of an IT as integral to his or her sense of self.” IT identity emerges through continuous interaction between individuals and IT, shaping perceptions and guiding behavior over time. In the context of repeated behavior, identity serves as a primary motivator, making IT identity a strong predictor of technology-related actions (Carter and Grover 2015; Carter et al. 2020; Qin et al.

2025). IT identity comprises three key dimensions: relatedness, emotional energy, and dependence. These capture the emotional and functional bonds individuals form with technology (Carter et al. 2020). Building on this concept, AI identity is defined as "the extent to which individuals perceive the collaboration with AI in the workplace as an indispensable component of themselves" (Cao et al. 2023; Mirbabaie et al. 2022, p. 77; Shonhe and Min 2025). Employees with a strong AI identity tend to engage more positively with AI, showing proactive behaviors (Qin et al. 2025). However, it can also lead to unintended consequences such as psychological entitlement and unethical behavior, especially when individuals perceive their AI identity as rare or superior (Cao et al. 2023). In organizational settings, AI Identity can both reinforce and threaten professional role identity. While some employees feel empowered by AI, others experience identity threats when AI replaces core tasks (Shonhe and Min 2025; Strich et al. 2021). Recent research highlights that AI identity significantly shapes how professionals reconstruct their role identity in response to AI integration, giving rise to diverse patterns such as alignment, ambivalence, dis-identification, or resistance (Richter and Schaller 2025).

2.3 Organizational and Cultural Influences on AI Usage

Besides individual-level characteristics, organizational and cultural factors significantly impact employee behavior concerning AI adoption (Venkatesh 2022). Organizational culture, defined as a set of shared values, norms, and practices within an organization (Schein 1990), can either promote or hinder transparent AI integration. Organizations characterized by openness, innovation, and transparent communication (Chesbrough 2010; Schein 2010) often foster ethical AI adoption, as these cultural factors generally support open discourse and experimentation (Yun et al. 2020) with new technologies. In contrast, hierarchical, traditional, or risk-averse organizations may unintentionally encourage employees to conceal their AI usage to avoid scrutiny or perceived threats to established hierarchies. Cultural contexts at the societal level broadly shape behavioral patterns in organizations (Zald et al. 2012), and they also specifically influence AI-related behaviors. For example, societies with stringent data protection regulations (Goddard 2017) and cautious attitudes towards innovation may experience slower or more concealed AI adoption. Similarly, competitive environments may often intensify concealment behaviors as employees attempt to maintain personal advantages or avoid negative social perceptions related to AI use.

3 Methodology

A qualitative approach was chosen to gain an in-depth understanding of how personality and identity factors interact with AI usage in organizational settings. Given the emergent nature of this topic and the limited existing research, an exploratory design was deemed appropriate (Creswell 2010). Qualitative methods enable the capture of nuanced perceptions and behaviors that might be overlooked in more structured approaches (Patton 2002).

3.1 Data Collection & Sample

The study included 23 experts from diverse fields such as academia, AI startups, consulting, engineering, and finance. These experts were primarily contacted via LinkedIn, where approximately 40 potential participants were invited to take part in the study. Ultimately, 23 experts agreed to participate, and the interviews were conducted between December 23, 2024, and March 4, 2025. The durations of live interviews ranged from 12:26 minutes (E1) to 93:06 minutes (E6), with an average length of 33:58 minutes. Written responses were completed individually by experts and submitted electronically, requiring an estimated average completion time of 21 minutes. Data collection concluded after 23 interviews upon reaching data saturation, defined as the point at which no new insights or themes emerged (Fusch and Ness 2015). An overview of all interviewees is provided here: https://doi.org/10.5281/zenodo.15706347.
An eleven-question interview guide was developed to explore how personality traits and AI identity influence employees' usage of GenAI tools like ChatGPT, as well as the potential ethical and strategic considerations that arise. An overview of the interview questions can be found here: https://doi.org/10.5281/zenodo.15012178. These key questions address topics such as the impact of Dark Triad traits on moral behavior, the reasons behind concealing AI usage, the role of competitive work environments and potential risks to organizations. While these constructs were explicitly mentioned in the interview questions, we acknowledge that this may have introduced confirmatory bias by directing participants' attention toward specific psychological themes, thus limiting the study's purely inductive nature. However, the semi-structured format allowed participants to steer the conversation and share experience-based perspectives, which helped surface unexpected themes. Prior to finalization, the interview guide was pretested with three participants (E1–E3) and refined for clarity and relevance with assistance from a student, ensuring comprehensibility across diverse professional backgrounds.

3.2 Data Analysis

Data were analyzed using the widely recognized Gioia methodology (Gioia et al. 2013) as a structured approach for conceptual development. The 23 interview transcripts contained 3670 text segments in total. In the initial coding pass, 248 first-order concepts were identified and applied 950 times across the transcripts, with some codes used only once and others assigned to multiple text passages. A second doctoral researcher reviewed the assigned codes to increase reliability, and the overlap-finding feature in MAXQDA revealed areas where codes converged. Following this review, 230 first-order concepts remained. These refined concepts were then consolidated into 15 second-order themes, which were ultimately distilled into 4 aggregated dimensions, providing the theoretical basis for the Trait-Identity Impact Framework. Both MAXQDA and Microsoft Excel were used throughout to systematically code, organize, and refine the data. The resulting data structure is illustrated in Figure 1. As researchers, we acknowledge that our disciplinary and professional backgrounds influenced the study's design and interpretation. The author's experience in a competitive banking environment, where GenAI was used strategically but rarely discussed openly, informed the focus on personality, identity, and concealment. While we remained open to emergent insights, our expectations may have shaped thematic emphasis. To reduce interpretive bias and strengthen credibility, we engaged in informal peer discussions during the analysis. We conducted a co-occurrence analysis to identify thematic overlaps within the interview data. The results revealed five text segments where the following themes frequently co-occurred: (1) AI-driven overconfidence, particularly in narcissistic individuals who misattribute AI outputs as personal expertise; (2) competitive pressure, which strengthens AI identification as individuals seek to maintain a professional edge; and (3) moral disengagement, especially in competitive environments, where AI concealment or unethical use is justified. These overlaps illustrate the interconnection between personality traits, competition, and AI-related behaviors. The full heatmap is available at: https://doi.org/10.5281/zenodo.15011966.

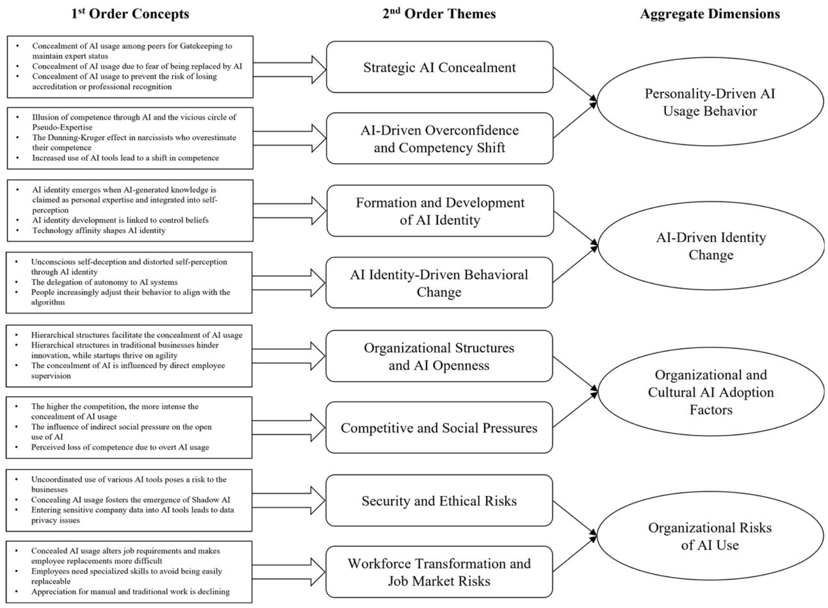

Figure 1. Data Structure of the expert interviews

4 Results

4.1 Thematic findings and the Trait-Identity Impact Framework

The findings are based on interviews with experts mainly from German-speaking Europe and reflect typical regional conditions, such as strict data protection norms, reserved AI attitudes, and hierarchical organizational structures. The aggregated dimensions and related second-order themes are outlined below.

Personality-Driven AI Usage Behavior

The first aggregated dimension, Personality-Driven AI Usage Behavior, illustrates how individual traits and dispositions guide employees' engagement with AI. ***Strategic AI Concealment*** captures how individuals deliberately hide or selectively disclose their AI use to maintain personal advantage or expertise status. For instance, one participant explained that ambitious individuals may frame the advantage of Generative AI as their own expertise to appear indispensable, since otherwise anyone could achieve similar results (E4). Related first-order concepts involve fear of replacement by AI, gatekeeping access to specialized knowledge, and avoiding professional scrutiny. Strategic AI Concealment reflects knowledge hiding, defined as the intentional withholding of requested information, often driven by competitive pressures or status concerns, ultimately undermining trust, creativity, and organizational learning (Connelly et al. 2012; Connelly et al. 2019). ***AI-Driven Overconfidence and Competency Shift*** focuses on how users develop an inflated sense of capability due to frequent AI reliance, often mistaking AI-generated outputs for personal expertise. One participant noted that individuals can present themselves as experts without possessing actual competence, as their knowledge is often derived from AI tools without deeper understanding. This can lead to a self-reinforcing cycle where perceived expertise continues to grow, making it difficult to admit a lack of real skills, especially in high-level positions (E16). The associated first-order concepts discuss the Dunning-Kruger effect (Dunning 2011), where certain personalities overestimate their abilities due to AI-assisted achievements. Recent research by Guan et al. (2025) supports this pattern, showing that increased reliance on generative AI can foster overconfidence.

AI-Driven Identity Change

The second aggregated dimension, AI-Driven Identity Change, highlights how ongoing interaction with AI reshapes an individual's self-perception and sense of professional identity. ***Formation and Development of AI Identity*** captures how individuals evolve a distinct AI identity by integrating AI-generated knowledge into their self-view (Cao et al. 2023; Carter et al. 2020). One expert notes that AI identity emerges when AI-generated knowledge is claimed as personal expertise and integrated into self-perception (E18). Another participant emphasizes that the formation of AI identity is closely linked to control beliefs whether individuals passively accept AI-generated outputs or actively seek to understand and regulate them (E20). ***AI Identity-Driven Behavioral Change*** highlights how a established AI identity can substantially shift day-to-day behavior. One interviewee indicated that AI identity can lead to unconscious self-deception and a distorted self-perception, as individuals may misattribute AI-generated outputs as their own (E13).

Organizational and Cultural AI Adoption Factors

The third aggregated dimension, Organizational and Cultural AI Adoption Factors, describes how broader societal, structural, and competitive elements affect AI usage within companies. ***Organizational Structures and AI Openness*** addresses the degree to which company hierarchies either enable or stifle transparent AI use. Several first-order concepts pointed to the tendency of traditional, top-down organizations to impede innovation. Thus making it easier to hide AI usage. Conversely, startups with flatter hierarchies encourage experimentation and open discussion about AI tools. One participant explained that in a rigid hierarchy, people fear supervision and keep their AI usage under wraps (E11). These findings align with prior research, which suggests that bureaucratic structures in mature corporations tend to hinder creativity and innovation, while startups are designed to foster agility and openness (Freeman and Engel 2007). ***Competitive and Social Pressures*** highlights how external and internal competition can drive employees to conceal or selectively reveal their AI usage. Some participants mentioned that intense rivalry pushes individuals to hide AI in hopes of gaining an edge, while others pointed to social perceptions, such as perceived loss of competence, if AI reliance becomes too visible. "The more intense the competitive situation within the employee structure of the company, the greater the concealment of AI usage.", noted one consultant (E13).

Organizational Risks of AI Use

The fourth aggregated dimension, Organizational Risks of AI Use, illustrates the negative consequences that can arise when AI is adopted without proper oversight or ethical considerations. ***Security and Ethical Risks*** highlights how uncoordinated AI usage fosters "Shadow AI" (Fürstenau and Rothe 2014) and raises concerns over data privacy. Several participants warned that entering sensitive company information into unverified AI tools can expose organizations to external threats and reputational damage. One interviewee emphasized that when employees do not disclose their use of AI tools, companies face increased risks of data protection violations, compliance issues, and security vulnerabilities (E23). These concerns are reflected in recent governance research on generative AI, which emphasizes the threats of Shadow AI and the urgent need for organizational oversight to mitigate data security and ethical risks (Dolci and Aguiar 2025; Feuerriegel et al. 2024; Haag and Eckhardt 2017). ***Workforce Transformation and Job Market Risks*** focuses on the evolving nature of job requirements caused by widespread AI integration. One expert (E4) described how concealed AI usage can create skill gaps, making it more challenging to replace or retrain employees effectively. One expert (E13) noted that increasing reliance on AI can lead to unrealistic time expectations. Those who frequently use AI tools may overlook the additional time needed by employees who rely less on such technologies, potentially creating imbalances in workload and efficiency perception (E13). Building on the four aggregated dimensions, we propose the Trait-Identity Impact Framework (Figure 2), which illustrates how personality traits, AI identity, and organizational and cultural factors jointly shape employee behavior in the context of GenAI. The framework conceptualizes these elements as part of a dynamic, recursive system. On the individual level, personality traits (e.g., narcissism) influence how employees develop an AI identity. This relationship is bidirectional: while personality shapes ai identity, a strong AI identity can reinforce traits like competitiveness or risk-taking over time.

Personality traits and AI identity both shape how individuals use GenAI tools, transparently or covertly. This behavior is further shaped by organizational and cultural factors such as leadership norms or innovation culture, which can support or inhibit visible AI usage and identity development. The link between AI identity and usage is also recursive: how people interact with GenAI affects how they see themselves, reinforcing or challenging their AI identity. AI usage behavior leads to organizational consequences, e.g., workflow changes or the emergence of shadow AI. These outcomes prompt organizational responses such as training or ethical guidelines. These responses, in turn, shape future behavior and influence the broader organizational context. Over time, these structures affect which behaviors and identities are seen as legitimate. Structural changes may also directly impact AI identity by redefining professional roles.

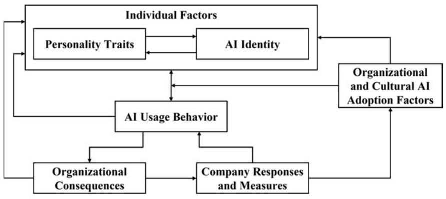

Figure 2. Trait-Identity Impact Framework: How personality, identity, and context shape AI usage and outcomes.

4.2 AI Identity Archetypes: Four Patterns of Identity-Based GenAI Use

In our expert interviews, we identified four archetypes of AI identity (Figure 3): Innovative Pioneers, Hidden Users, Transparent Users, and Critical Skeptics. Innovative Pioneers strongly identify with AI and openly disclose its use, viewing transparency as key to innovation. Hidden Users likewise identify with AI but conceal their usage, often to maintain a competitive edge or appear more competent. Transparent Users disclose their use but treat AI as a tool rather than part of their identity. Critical Skeptics neither identify with AI nor disclose its use, remaining cautious or skeptical. These archetypes help explain differing approaches to GenAI adoption and transitions between roles over time. Conceptually, they sit at the intersection of AI Identity and AI Usage Behavior within the Trait-Identity Impact Framework (Figure 2), reflecting varying degrees of identification and disclosure and linking internal identity with external behavior.

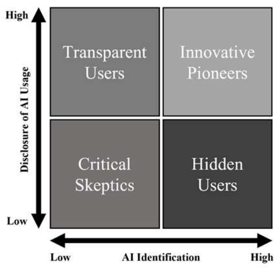

Figure 3. Matrix of AI Identity Archetypes

5 Discussion

5.1 Theoretical Implications

This study contributes theoretically by exploring how personality traits, AI identity, and organizational culture collectively shape generative AI adoption behaviors. Building on initial claims, findings confirm that Dark Triad traits significantly drive strategic concealment and unethical AI use. Moreover, results extend identity theory (Cao et al. 2023; Carter and Grover 2015) by revealing how social recognition and competitive contexts actively shape AI identity, aligning with initial expectations. Additionally, this study underscores how innovation-friendly organizational cultures support ethical AI usage, whereas hierarchical, risk-averse cultures foster concealment behaviors.

5.2 Practical Implications

From a practical perspective, this research offers valuable insights for organizational leaders aiming to integrate AI technologies responsibly. Organizations should foster supportive and transparent cultures that actively encourage ethical AI practices. This can be achieved through clearly defined governance frameworks, targeted training, continuous education, and open communication strategies. Encouraging a critical and reflective AI literacy among employees helps mitigate potential risks such as ethical violations, strategic concealment, and overreliance on AI. Thus, organizations can effectively manage the adoption of generative AI by understanding and strategically responding to the complex influences identified in this study. These recommendations align with initial assertions emphasizing the necessity of addressing complex personality and contextual influences to ensure responsible AI integration.

5.3 Limitations and Directions for Future Research

Despite its contributions, this research has limitations. Primarily, the qualitative design and the sample size (23 interviews) restrict generalization to broader populations, though theoretical generalization remains feasible (Lee and Baskerville 2003). Future research should adopt larger quantitative or mixed-methods studies to enhance validity and cross-contextual applicability. Although diverse, the sample predominantly reflects European perspectives, warranting further investigation in different global contexts to explore cultural nuances. An especially promising avenue for future research is the deeper examination of AI identity, exploring how diverse archetypes or distinct manifestations of AI identities may emerge within organizational settings. This includes considering how not only AI agents but also employees consciously or unconsciously develop varying forms of AI identities, influenced by regular interactions with AI tools. Investigating these AI identities further can offer valuable insights into managing AI integration strategies more effectively and ethically. In retrospect, more behaviorally oriented and neutral questions may have allowed participants to refer to psychological mechanisms more freely. Future research should consider this and avoid naming constructs explicitly to safeguard inductive depth and interpretive authenticity. We also acknowledge our own role as researchers in shaping data collection and interpretation and have sought to remain reflexive throughout the analysis. While the sample included experts from various industries, the geographical focus was primarily European, with a strong emphasis on German-speaking contexts. The findings therefore reflect cultural and regulatory conditions typical of Europe, such as stricter data protection norms (e.g., GDPR) and a cautious approach to innovation etc. These factors likely influenced how GenAI is adopted and communicated in workplace settings. The study's cultural and regulatory insights should thus be interpreted within a European frame. In high-tech, low-regulation environments such as the U.S. or parts of Asia, where AI adoption is faster and more commercially driven, behaviors and identity dynamics around GenAI use may differ. Future research should explore these regional differences to assess the applicability of the Trait-Identity Impact Framework across diverse contexts.

6 Conclusion

This study provides a comprehensive understanding of the complex interactions between personality traits, identity, and organizational and cultural contexts affecting employee behavior towards generative AI technologies. By integrating qualitative insights from expert interviews, the research highlights the significance of personality-driven behaviors, identity formation processes, and environmental conditions, emphasizing transparent and ethical AI use. Organizations are encouraged to adopt structured governance, supportive cultures, and targeted training to effectively navigate these multifaceted dynamics. Addressing these factors holistically can enhance organizational effectiveness, foster responsible AI adoption, and better prepare employees for ongoing digital transformation.

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