Innovating with publicly available LLMs at work: A lifespan perspective

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Abstract

This study examines how various facets of user's age, i.e. chronological age, professional age and organizational tenure, shape the use of publicly available large language models chatbots (LLMs) at work. Adopting a lifespan perspective, we analyze how combinations of the different facets of age, alongside AI literacy and job autonomy explain extent and innovative LLM use. Using fsQCA on data from the U.S.-based professionals, we identify multiple equifinal pathways to LLMs use. The findings reveal that while chronological age plays a role, it does not operate in isolation. The extent of LLM use is more age-sensitive, with different pathways for younger and older employees, whereas innovative use is driven more by contextual and experiential conditions. Overall, younger workers require high AI literacy, autonomy and longer tenure, while older employees are driven by high AI literacy and shorter tenure. Our results contribute to the research on LMM use in the workplace by providing a nuanced understanding of the role of age.

Keywords: Large language models, Chatbots, Artificial intelligence, innovative use, Generative AI, Age, AI literacy, fsQCA

1. Introduction

Publicly available LLM chatbots, such as ChatGPT, Claude and Copilot have made large-scale inroads to workplaces. Compared to prior generations of artificial intelligence based tools, LLM chatbots are remarkably flexible. Their general-purpose nature means they can be adapted to a wide range of tasks and continuously reshaped through interactive prompting. These tools can be applied effectively in tasks such as creative writing, data analysis, communication and problem-solving ideation (Bilgram & Laarmann, 2023). While formal organizational adoption of LLM chatbots has been gradual, primarily due to resource constraints and governance concerns, actual usage within workplaces is already widespread (Humlum & Vestergaard, 2025) as employees are increasingly using publicly accessible LLM chatbots to enhance their productivity (Peng et al., 2023).

Although LLM chatbots are accessible to anyone with an internet connection, their workplace value hinges on effective use. Recent studies suggest that the benefits of LLM chatbots may not be equally distributed across generations (Shin & Bang, 2025). It is commonly acknowledged that older individuals tend to be less likely to adopt new technologies, often citing lower digital self-efficacy, concerns about complexity and reduced motivation to experiment with unfamiliar systems (Niehaves & Plattfaut, 2013). Prior research implies that these tendencies may hold for new AI tools as well. Wang et al. (2025) report that older adults show stronger negative attitudes toward LLM chatbots like ChatGPT. A large-scale survey in Denmark by Humlum and Vestergaard (2025) found that each additional year of age was associated with a lower probability of having used ChatGPT at work. Such evidence reinforces the perception of age as a constraining force in LLM adoption and use.

Yet, recent research also reveals that the relationship between age and LLM chatbot use is more complex than traditionally assumed. For example, Peng et al. (2023) found that older employees experienced the highest productivity from using AI tools like Copilot, challenging the notion that younger, tech-savvy users always gain the most. Similarly, Kobiella et al. (2024) examined younger workers' experiences with ChatGPT and discovered that adoption and effectiveness were far from universal. While some younger employees reported increased productivity, others experienced reduced performance due to lack of challenge and dissatisfaction with the quality of responses (Kobiella et al., 2024).

Given this mixed empirical evidence, there is a pressing need to take a more nuanced perspective on age with respect to LLM chatbot use in the workplace.

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Much of the current literature centers on chronological age as a linear variable, often overlooking its interaction with the broader work and life based experiences that develop over time. Aging is inherently relational and unfolds with other time-based developmental experiences such as organizational tenure and career duration (North, 2019). These factors accompany aging and represent distinct forms of accumulated knowledge, contextual familiarity and professional maturity that can shape how individuals approach emerging technologies. Recognizing this and drawing from lifespan development theory (Kanfer & Ackerman, 2004; Rietzschel et al., 2016), this study adopts a broader conceptualization of age and investigates *how user's age, conceptualized as a combination of chronological age and developmental conditions of organizational tenure and professional experience, shape employees' usage of publicly available LLM chatbots at work*.

In addition to the age-related factors, we incorporate two key individual and contextual factors, AI literacy and job autonomy. These factors are particularly salient in an age-sensitive analysis because they can condition how age-related strengths or limitations manifest in employee behavior (Ng & Feldman, 2015). For instance, AI literacy may enable older employees to translate their accumulated expertise into effective LLM chatbots use, while job autonomy may provide the latitude required for younger or less experienced workers to experiment.

Our findings contribute to the emerging body of knowledge on LLM chatbot adoption and use (e.g. Camilleri, 2024; Gupta et al., 2024; Humlum and Vestergaard, 2025; Peng et al. 2023; Wang et al. 2024) by a more comprehensive account of how age interacts with individual and contextual factors to shape LLM chatbot use in the workplace. We use the shorthand "LLM use" in the remainder of this paper to refer to employees' interaction with LLM based chatbots.

2. Literature review

2.1 LLM use at workplace

LLMs are advanced AI systems trained on huge datasets to support a wide range of tasks (Russel, 2021). Based on transformer architecture, these models process input using self-attention mechanisms, allowing them to understand context and generate human-like responses. Unlike custom or purpose-built LLMs that are developed for specific functions within organizations, such as customer service, general-purpose LLMs are not tailored to a particular task. Consequently, they require users to independently identify where and how they can be applied. This flexibility increases the scope of LLMs application but also makes them challenging to use.

LLM use in the workplace has attracted scholarly attention, with research examining both the technical and social factors driving adoption (e.g. Camilleri, 2024; Jo & Park, 2023; Ma et al., 2025). From a technical perspective, prior research has found that system characteristics such as perceived usefulness, ease of use, credibility, knowledge support and contextual responsiveness shape users' willingness to engage with LLMs (Camilleri, 2024; Gupta et al., 2024; Ma et al., 2025). Concurrently, social aspects such as organizational culture, social influence and public perception toward AI are also found to be important (Jo & Park, 2023). Positive peer evaluations and coworker recommendations can legitimize LLM use, especially when early adopters share productivity gains and successful applications (Jo & Bang, 2023).

There is little research on the use of LLM across age groups. Studies that include age typically do so without making age the primary focus (e.g. Peng et al., 2023; Want et al., 2025). The results of these studies are often contradictory and inconclusive as discussed earlier. The perception of age is primarily influenced by traditional technology adoption research in general. Information systems research has documented lower adoption rates among older adults for new technologies (Czaja & Lee, 2007; Fox & Connolly, 2018; Morris & Venkatesh, 2000). Older workers often report less motivation to experiment with new information systems unless there is clear alignment with their job roles or immediate needs (Hill et al., 2008). While younger users tend to evaluate technologies based on performance and functionality, older professionals emphasize training, clarity of purpose and the relevance of the tool to their work environment (Soja & Soja, 2017). Overall, these traditional accounts tend to frame age primarily as a constraint and focus narrowly on chronological years, overlooking the broader developmental trajectories of life and contextual factors that can shape how individuals engage with emerging technologies such as LLMs.

2.2 Lifespan perspective on age

The lifespan approach conceptualizes age from an adult development perspective, in which aging encompasses parallel patterns of growth and decline in various human capabilities and knowledge (Rietzschel et al., 2016). A central tenet of this approach is the

recognition of dual cognitive trajectories, fluid intelligence (Gf) and crystallized intelligence (Gc) (Kanfer & Ackerman, 2004). Gf underpins reasoning, processing of novel information and the ability to handle novel tasks. It typically declines with age due to biological and neurological changes. In contrast, Gc encompasses accumulated domain knowledge, comprehension and experiential understanding. It tends to increase over time due to life experiences, repeated task exposure and the integration of experience into long-term memory (Ackerman, 1996; Kanfer & Ackerman, 2004).

These capabilities can offset each depending on the context (Kanfer & Ackerman, 2004). For example, the reduced flexibility and slower information processing associated with lower Gf that comes with aging might be offset by the domain expertise and procedural familiarity associated with higher Gc. Conversely, it is also possible that high levels of Gc may not fully compensate for age-related declines in Gf and may even amplify certain limitations. For example, an older employee with deep domain expertise (high Gc) may rely heavily on established routines and knowledge, which could hinder the experimentation needed to effectively prompt and adapt LLMs for novel tasks.

Given these dynamics, the lifespan approach perspective suggests that understanding the influence of age on workplace behaviors, such as the use of LLMs, requires accounting for both growth and decline (Kanfer & Ackerman, 2004). Rather than treating age as a singular constraint or asset, the lifespan approach emphasizes the importance of examining how developmental gains and losses interact over time. In this study, we operationalize this perspective by incorporating not only chronological age but also professional experience (career age) and organizational tenure, which serve as proxies for accumulated expertise and contextual familiarity. Although these three factors are naturally related, they do not necessarily move in lockstep. Recent data from the U.S. Bureau of Labor Statistics show that median employee tenure has decreased over time, suggesting that workers are changing employers more frequently (USBLS, 2024). Including all three dimensions offers a more comprehensive lens through which to analyze age-related differences in LLM engagement.

2.3 AI literacy and job autonomy

Alongside age, this study considers two additional factors, job autonomy and AI literacy. These factors are particularly relevant for the adoption and use of technologies that are voluntary in nature, such as publicly available LLMs. Prior research in the Information Systems literature has consistently identified both autonomy and user literacy as critical enablers of technology engagement (Ahuja & Thatcher, 2005; Ohashi et al., 2024). Job autonomy, defined as the extent to which individuals can determine how they perform their work, has been linked to greater innovation and discretionary technology use. For older employees in particular, high autonomy can unlock the potential to apply accumulated experience in creative ways. AI literacy, encompassing the skills, knowledge and confidence needed to understand and interact with AI tools, similarly shapes employees' capacity to make meaningful use of AI tools (Wang et al., 2022). Including these two factors offers a more context-sensitive view of how age influences both extent and innovative use of LLM in the workplace.

2.4 Conceptualization of LLM use

This study conceptualizes LLM use along two dimensions, extent of LLM use and innovative use of LLM. Extent of LLM use reflects employees' frequency, duration and intensity of engagement with LLMs in workplace tasks. This conceptualization is consistent with what prior research has termed lean measure of system use (Burton-Jones & Straub, 2006. While this dimension captures the magnitude of technology use, it offers limited insight into the richness or creativity of that engagement. To address this limitation, our measurement of LLM use includes a second dimension, innovative use, which captures more explorative and creative interactions with LLMs. This involves leveraging LLM capabilities to experiment with new ideas, reframe problems, or apply the technology in novel ways that go beyond established routines. Innovative use aligns with concepts such as deep structure use and cognitive absorption (Agarwal & Karahanna, 2000; DeSanctis & Poole, 1994) and mirrors the distinction between exploitative and explorative use found in organizational learning literature (Shao et al., 2020).

3. Research model

3.1 Chronological age

Chronological age refers to an individual's biological age, measured by the number of years since birth. It is the most commonly used indicator of aging in Information Systems research (Morris et al., 2005).

As people grow older, they typically experience a decline in fluid cognitive abilities such as processing speed, working memory and mental flexibility (Kanfer & Ackerman, 2004). These changes can make it more challenging to deviate from routine and adapt to new technologies, particularly those requiring frequent interaction or navigation of unfamiliar features as is common in general-purpose LLMs. As such, higher chronological age may lead to lower use of LLMs, especially when their application is self-initiated and cognitively demanding. Similarly, reduced fluid cognition may limit older individuals' ability to experiment with or repurpose LLMs in creative ways, making it less likely that they engage in innovative use. Without supportive enablers, older age may be less likely to drive extensive and innovative use of LLMs.

3.2 Professional age

Professional age or career length refers to the number of years an individual has spent in a specific profession or occupational field. It reflects domain-specific expertise and accumulated knowledge developed over time (Widén et al., 2020). From a lifespan perspective, career age is closely linked to crystallized intelligence (Gc), which tends to grow through sustained task repetition and professional experience (Kanfer & Ackerman, 2004). This accumulated expertise can support more effective identification of use cases for new technologies like LLMs. Employees with long professional experience can be better equipped to recognize where LLMs can be applied meaningfully in their work, which may lead to higher levels of LLM use, particularly when LLMs are used to complement well-understood tasks. At the same time, extensive domain knowledge can also enable more nuanced or creative applications of LLMs, potentially leading to innovative use when individuals are motivated to explore new approaches or reframe problems. However, the routinization of tasks and adherence to established workflows that often accompany higher professional age may also reduce openness to experimentation. Thus, both low and high professional age may appear in configurations that support both extent and innovative LLM use.

3.3 Organizational tenure

Organizational tenure refers to the number of years an individual has spent within their current organization. It reflects familiarity with internal structures, norms, processes and technologies, as well as embeddedness within an organization's social and technical systems (Ng & Feldman, 2010). From a lifespan perspective, longer tenure contributes to crystallized, context-specific knowledge that enables employees to navigate established processes more efficiently and with greater confidence in an environment (Kanfer & Ackerman, 2004). This enhanced familiarity can lead to greater comfort in trying out non mandated tools like LLMs, thereby supporting higher use. In addition, the organizational knowledge and informal influence that often come with longer tenure can empower employees to experiment more freely and apply LLMs in novel ways. Thus, longer tenure can facilitate both the extent of use and the innovative use of LLMs.

3.4 Job autonomy

Job autonomy is defined as the degree to which an individual controls his or her work and decision-making processes (Hackman & Oldham, 1975). Autonomy is recognized as a critical enabler of system use, particularly in environments where employees must self-direct how they integrate digital tools into their tasks (Ahuja & Thatcher, 2005). Employees with higher job autonomy often experience greater psychological ownership and intrinsic motivation, which can lead them to invest more effort in learning and applying new systems (Liang et al., 2015). This freedom can foster risk-taking and exploratory behavior, which are necessary for engaging deeply with the capabilities of publicly available LLMs. As such, higher job autonomy can lead to increased use of LLMs by enabling employees to incorporate them into their workflows with greater flexibility. It can also lead to greater innovative use, by allowing individuals to experiment with novel applications and discover unique ways to derive value from LLMs. In contrast, employees with low autonomy are likely to feel constrained by rigid procedures or lack the discretion to try new tools, thereby limiting both their engagement with LLMs.

3.5 AI literacy

AI literacy refers to an individual's ability to understand, evaluate and effectively and ethically use AI (Wang et al., 2022). Although the concept is relatively new, it is increasingly recognized as a critical condition for meaningful engagement with AI technologies (Schiavo et al., 2024). Higher AI literacy is positively associated with greater willingness and

readiness to adopt AI tools (Pan et al., 2025). A key premise is that AI literacy lowers the perceived complexity of AI systems and equips individuals to recognize their practical benefits, thereby making them more approachable and usable (Wang et al., 2022). In the context of LLMs, employees with greater AI literacy can be inclined to use these tools frequently and intensively, as their competence in navigating the systems makes them more confident and efficient users. This ease of use can reinforce positive experiences, leading to habitual engagement and, over time, greater use of LLMs. Moreover, AI-literate individuals are better positioned to explore the boundaries of LLM functionality. Their understanding of the strengths and limitations of AI systems, including issues such as AI hallucinations (Maleki et al. 2024) allows them to craft more effective prompts and experiment with novel strategies. This capacity to work around known weaknesses while leveraging advanced features can lead to greater innovative use.

3.6 Configurational research approach

Age is frequently treated as a linear predictor in technology adoption studies (e.g. Czaja & Lee, 2007; Fox & Connolly, 2018; Morris & Venkatesh, 2000). From the lifespan perspective, the three interrelated age facets do not operate in isolation. They interact with each other as well as with contextual enabling conditions, AI literacy and job autonomy, to shape technology-related behaviors. The interplay of these conditions can create multiple alternative causal configurations of conditions explaining LLM usage at work. For example, younger employees with limited career experience might achieve high innovative use of LLMs through high AI literacy and autonomy, while older employees with extensive career and tenure may reach the same outcome through accumulated domain knowledge and strategic integration.

To examine these potential complex interdependencies, this study uses a configurational approach with fuzzy-set qualitative comparative analysis (fsQCA). This approach is particularly suited for identifying configurations of conditions that jointly lead to an outcome, accommodating both equifinality, the idea that multiple different combinations can produce the same result and causal asymmetry, whereby the presence or absence of a condition may matter differently depending on the context (Misangyi et al., 2017; Ragin, 2008). This approach allows the study to move beyond additive effects and examine how different age dimensions can amplify, substitute for, or constrain one another in the presence of enabling or inhibiting conditions. Figure 1 presents a conceptual map of these intersecting pathways.

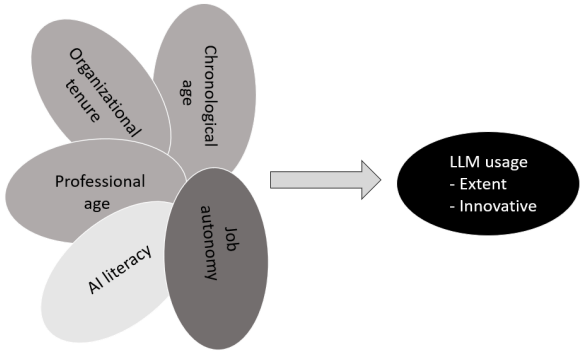

Figure 1. The Configurational model

4. Methodology

4.1 Data collection

The data for this study were collected through an online survey administered via Prolific, a widely used platform for academic research (Palan & Schitter, 2018). The sample consisted of U.S.-based professionals who reported using publicly available LLMs for work-related tasks within the past month. We used screening questions to ensure participant eligibility and two attention-check items to ensure data quality. The final dataset comprised 413 valid responses after excluding incomplete submissions and those that failed attention checks. The average completion time was approximately 10 minutes.

The sample included 60% male and 39.5% female respondents, with 0.9% preferring not to say. In terms of education, 75.3% held a college or university degree. Respondents represented organizations of different sizes, with 27.4% working in organizations with fewer than 50 employees, 26.1% in organizations with 50–249 employees, and 46.5% in organizations with 250 or more employees. The largest industry sectors in the sample were information and communication technology (18.6%), education (11.9%), and financial and insurance services (11.1%).

4.2 Measures

All variables or conditions were measured using validated multi-item scales drawn from prior research. Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Innovative use was measured using items from Li et al., (2013). The extent of LLM use measures were adopted from Venkatesh et al., (2012) and consisted of

a formative index of three items, frequency, duration and intensity of LLM use for work-related tasks. As the extent of LLMs was modeled as a formative construct, we used latent variable scores obtained through PLS-SEM to accurately capture the weighted contribution of its indicators for fsQCA analysis (Rasoolimanesh et al., 2021).

The key explanatory variables were the three dimensions of age: chronological age (measured in years), career age (years of experience in the respondent's current profession) and organizational tenure (years spent in the current organization). In addition, AI literacy was assessed using a scale adapted from Wang et al. (2022). Job autonomy was measured with three items based on scale from Wang and Netemeyer (2002). Descriptive statistics of all constructs are presented in Table 1.

Table 1. Descriptive statistics

Conditions	Min	Max	Mean	10 P	50 P	90 P
Chronological age	18.00	70.00	39.40	25.00	38.00	56.00
Organizational tenure	0.00	39.00	7.62	1.00	5.00	17.60
Professional age	0.00	45.00	12.05	2.00	9.00	26.00
Job autonomy	1.00	5.00	4.03	3.00	4.00	5.00
AIL	1.00	5.00	4.00	3.42	3.98	4.69
Extent of LLM use	-1.52	3.78	0.00	-1.12	-0.06	1.11
LLM innovative use	1.00	5.00	3.76	2.75	4.00	4.75

Notes: P = percentile; Negative values of extent of LLM use indicate below-average LV standardized scores, not negative usage.

4.3 Reliability and validity

Prior to conducting fsQCA, reliability and validity checks were performed. Reflective constructs, AIL, job autonomy and innovative use were assessed for internal consistency using Cronbach's alpha and composite reliability, with values exceeding the accepted thresholds of 0.70 (Hair et al., 2022). Convergent validity was evaluated using the average variance extracted, with all constructs meeting the minimum requirement of 0.50. Discriminant validity was assessed using the Heterotrait–Monotrait Ratio of Correlations and all values remained below the conservative threshold of 0.85, confirming adequate discriminant validity (Henseler et al., 2015).

The extent of LLM use construct was modeled as a formative construct. Following the guidelines by Hair et al. (2022), formative validity was assessed by examining the outer weights and multicollinearity statistics. All indicators demonstrated significant outer weights, confirming their relevance to the construct. Variance inflation factor values were well below the threshold of 5, indicating no issues with multicollinearity. Moreover, all pairwise correlations were below the threshold of 0.80 (Pappas & Woodside, 2021). This indicates that there is no redundancy and that each construct contributes uniquely to the fsQCA. Together, these assessments provide strong support for the reliability and validity of the measurement model.

4.4 Set-Theoretic Analysis with fsQCA

The fsQCA was used to examine how employees' engagement with LLMs emerges from combinations of age-related and contextual attributes. FsQCA is a set-theoretic method that treats conditions and outcomes as sets with varying degrees of membership, allowing us to assess whether particular combinations of conditions are sufficient to produce an outcome (Collan, Fedrizzi, & Kacprzyk, 2016; Ragin, 2008). This perspective shifts attention away from estimating net effects, as in regression, and instead follows the neoconfigurational view that outcomes result from causal combinations rather than isolated factors (Misangyi et al., 2017). Thus, rather than analyzing each attribute separately, we examine how chronological age, professional tenure, organizational tenure, AI literacy, and job autonomy collectively form alternative pathways to high extent and innovative use of LLMs.The fsQCA analysis was conducted using the fsQCA 4.1 software (Ragin, 2008).

4.5 Data analysis

For the data analysis we followed the fsQCA analysis procedure as outlined in previous research (Ragin, 2008). The first step involved calibrating all raw data into fuzzy-set membership scores ranging from 0 (full non-membership) to 1 (full membership). This required setting three anchor points: thresholds for full membership, full non-membership and a crossover point indicating maximum ambiguity in set membership. Given the skewed nature of the data, a percentile-based calibration approach was applied (Pappas & Woodside, 2021). Accordingly, the 90th percentile was set for full membership, the 10th percentile for full non-membership and the 50th percentile for the crossover point. To address potential ambiguity at the crossover threshold, a constant of 0.001 was added (Fiss, 2011).

After calibration, the next step is creating a truth table, where each row represents a unique combination of causal conditions. For the sample size of this study (N = 413), a minimum frequency threshold of four cases was applied, which is consistent with

recommendations for medium-to-large samples (Ragin, 2008). Two key criteria, frequency and consistency, were used to refine the table. Frequency indicates how many cases exhibit a given configuration, and consistency measures how reliably a configuration leads to an outcome (Fiss, 2011). The consistency threshold was set at 0.85 and the proportional reduction in inconsistency (PRI) was set at 0.60 to minimize contradictory configurations.

5. Results

Before fsQCA analysis we performed a necessary condition analysis and found no necessary conditions, as none of the conditions had a consistency greater than the threshold of 0.90 (Pappas & Woodside, 2021).

The results for both extent and innovative LLM use are presented in Tables 2 and 3 using Ragin's (2008) notation system. We report the intermediate solution, which balances theoretical and empirical considerations. Filled circles indicate the presence of a condition, empty circles its absence, and blank cells its irrelevance within a configuration. Large circles represent core conditions central to the outcome (appearing in both parsimonious and intermediate solutions), while small circles indicate peripheral conditions that are complementary (appearing only in the intermediate solution). Each column represents a configuration sufficient for the outcome.

Table 2. Configurations for high extent of general purpose LLMs use at work

	GU1	GU2	GU3	GU4
Chronological age	●	●	○	●
Organizational tenure	○	○	●	
Professional age	○			○
Job autonomy		•	●	•
AIL	●	●	●	●
Raw Coverage	0.25	0.26	0.28	0.24
Unique Coverage	0.04	0.04	0.08	0.01
Consistency	0.85	0.83	0.84	0.85
Solution coverage		0.41		
Solution consistency		0.80		

The fsQCA identified four distinct configurations that lead to high LLM use and two configurations that lead to innovative use of publicly available LLMs in the workplace. The solutions' consistency exceeds the recommended threshold of 0.75 (Ragin, 2008), indicating that the configurations reliably explain the extent and innovative use of LLMs.

Regarding extent of LLMs use, four distinct configurations (GU1–GU4) were identified, each representing a unique pathway to high engagement. Configuration GU1 highlights a scenario in which older employees actively use LLMs when they have relatively short organizational and career tenure but demonstrate high AI literacy. Configuration GU2 builds on this pattern by adding job autonomy as a supporting condition, indicating that older individuals with low organizational tenure and high AI literacy are more likely to use LLMs regularly when they also enjoy discretion in how they perform their work. Configuration GU3 presents a contrasting profile. Here, younger employees with longer organizational tenure, high job autonomy and AI literacy exhibit high use of LLMs. Finally, configuration GU4 once again focuses on older individuals, demonstrating that a short career in a profession, coupled with high AI literacy and autonomy, also results in frequent LLM use.

A cross-comparison of the four configurations indicates that three conditions, chronological age, organizational tenure and AI literacy are central conditions in shaping the extent of LLM use at work, frequently appearing as core factors. Configurations GU1, GU2 and GU4 are about older employees and suggest that chronological age needs a counterbalance in the form of being relatively new to the organization or profession, along with autonomy that enables experimentation. In contrast, for younger employees, the extent of LLM use appears to require longer organizational tenure and high autonomy. This is likely because this combination offers the confidence, contextual awareness and latitude needed to apply LLMs effectively in daily tasks.

Regarding high innovative use of LLMs in the workplace, the fsQCA analysis identified two distinct configurations. Configuration IU1 identifies a pathway where employees engage in creative applications of LLMs when they have high organizational tenure and low professional age, along with high AI literacy and job autonomy. In this configuration, chronological age is irrelevant. Configuration IU2 is specifically about young employees who depict innovative use of LLMs when they have long organizational tenure, high job autonomy and strong AI literacy.

A cross comparison shows that high AIL and long organizational tenure are critical for innovative use of LLMs at work. There is no older employees specific configuration but for younger employees there is one that is exactly the same as for the extent LLM use. The overall solution coverage for the extent and innovative LLM use is relatively low, indicating that the configurations explain only a subset of cases. Thus, the

findings reveal partial but theoretically meaningful pathways within the broader phenomenon.

Table 3. Configurations for high innovative use of general purpose LLMs at work

	IU1	IU2
Chronological age		○
Organizational tenure	●	●
Professional age	○	
Job autonomy	•	●
AIL	●	●
Raw Coverage	0.30	0.32
Unique Coverage	0.03	0.05
Consistency	0.85	0.87
Solution coverage	0.35	
Solution consistency	0.85	

We performed sensitivity analysis and repeated the fsQCA with alternative calibration anchors, consistency and frequency thresholds. While this produced more configurations under lower thresholds, the overall patterns and interpretations remained stable.

6. Discussion

This study offers several theoretical contributions to both the emerging literature on LLM use in organizations and the broader domain of age and technology use research.

6.1 Theoretical implications

First, the study contributes to research on the use of publicly available LLMs in the workplace (e.g. Camilleri, 2024; Gupta et al., 2024; Humlum & Vestergaard, 2025; Peng et al. 2023; Wang et al. 2024). It demonstrates that age, a factor typically relegated to a secondary level of importance, is in fact important in shaping LLM use. Age interacts with other individual and contextual factors and contributes in unique ways to the uptake and application of LLMs. Importantly, different conditions matter differently for distinct age groups. For younger employees, being deeply embedded in the organization and having job autonomy enhance their extent and innovative use of LLMs. Conversely, older employees are driven by being newer to the organization or entering mid-career, conditions that can mitigate age-related constraints. Critically, AI literacy emerges as essential for effective LLM use for both young and old employees.

Second, the study challenges the notion that younger employees are naturally more inclined toward LLM use at work (see Draxler et al., 2023). The configurational results indicate that older employees can also be frequent and even innovative users of LLMs, provided that they have autonomy at work and possess adequate AI literacy. Conversely, younger employees are unlikely to engage with LLMs in meaningful ways unless they are institutionally embedded and feel confident using AI tools. Multiple age-related factors interact highlighting that the role of age is far more nuanced and dynamic than traditionally conceived in prior research.

Third, while much research on publicly available LLMs focuses on basic adoption (e.g. Humlum & Vestergaard, 2025; Jo & Park, 2024; Ma et al., 2025), their innovative use remains underexplored. The findings advance the understanding in this area by analyzing innovative use along with the extent of LLMs use, albeit in the context of age. Distinct dynamics underlie the two types of LLM usage. The extent of LLM use is more sensitive to chronological age, whereas innovative use depends more on contextual and experiential factors like organizational tenure, AI literacy and job autonomy. For younger employees, the same conditions enable both types of use, suggesting that with adequate support, they more easily shift from routine to creative engagement. At the same time, for innovative use there is no old age specific configuration indicating that innovative use can be achieved regardless of old age when other enabling conditions are present. These findings advance theorizing on differentiated uses of generative AI in the workplace and highlight the importance of distinguishing between regular and innovative use in future research.

Lastly, the findings make an important, albeit secondary, contribution to the literature on AIL and the generational digital divide (e.g., Pinski & Benlian, 2023; Wang & Sun, 2024). AIL emerged as a core condition in configurations for regular and innovative use for younger and older employees alike. These results highlight AIL as a critical enabler of effective LLM use and a potential equalizer that can reduce age-related disparities in adoption and experimentation. These findings align with recent observations that AIL will play a critical role in minimizing the age-driven digital divide in the era of AI (Wang & Sun, 2024).

6.2 Practical implications

The findings of this study provide organizations with several actionable steps to support employees' use of publicly available LLMs at work. Organizations should recognize that older and younger employees

have different needs at various career stages. Investing in AI literacy training can help both younger and older employees in efficient and innovative uses of LLMs. Providing structured organizational support and onboarding can particularly help younger employees build the confidence and contextual understanding needed to leverage LLMs fully.

6.3 Limitations and future research directions

Our empirical research focused only on professionals based in the U.S. Moreover, we did not incorporate industry sector or organization size in the empirical research. It seems plausible to assume that there are differences in LLM use across industry sectors and organizations of different sizes. Future research could thus incorporate additional variables such as industry sector and organization size in the empirical measurement. Another limitation is the relatively low solution coverage in the fsQCA analysis. Future research could examine additional age sensitive factors such as technology anxiety and openness to change to develop a more comprehensive model.

Besides the future research directions stemming from the limitations of the present study, the use of publicly available LLMs that are to a significant degree out of organization's direct control can be considered a manifestation of the shadow IT phenomenon (see. Haag & Eckhardt, 2017). The risks related to IPR, privacy, and information security, stemming from uncontrolled, ungoverned LLMs use are a noteworthy challenge for organizational IT and AI governance. As a result we recommend directing scholarly attention to the organizational governance of LLM use to expand the domain organization organizational AI governance (Mäntymäki et al., 2022).

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