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Evolutionary modeling reveals that value-oriented knowledge creation behaviors reinvent jobs

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Recently, the strong artificial intelligence-based augmented capability enables the autonomous completion of traditional jobs devoid of human intervention, impacting labor markets. However, the underlying mechanisms have not been explored enough in prior research. In this research, we propose a computational model, focusing on the interplay between world knowledge networks and organizational knowledge sets, along with external labor market conditions. This model incorporates dynamic knowledge creation behaviors and is validated using a substantial dataset from a leading online recruitment platform in China, featuring over 20 million job postings and 1 million skill-related keywords. The results demonstrate that swift knowledge search and emulating knowledge within existing jobs are the main methods in the early developmental stage of organizations, accounting for about 75% of all simulation samples and forming the initial job evolution. As organizations progress, although fine-tuning the knowledge within existing jobs still remains significant, the intensity of knowledge search declines significantly, and the intensity of knowledge reuse surpasses that of knowledge search, reaching ~1.5 times its intensity during the stable phase. We also perform several parameter experiments and a case study to illustrate how jobs evolve in the labor market with different characteristics. The robustness tests demonstrate the model's resilience across different simulation environments and organization strategies. Our study underlies the mechanisms of job evolution from the organizational level and provides empirical evidence and insights into the job evolution dynamics within knowledge networks.

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Introduction

In the contemporary dynamic labor market, job reinventions and their evolution always stand as a pivotal determinant influencing the overarching dynamics and competitiveness within industries and organizations (Jesuthasan and Boudreau, 2018, Nature, 2017). The advent of cutting-edge digital technologies, exemplified by the Generative Pretrained Transformer (GPT), has significantly augmented the creativity of artificial intelligence (AI), enabling the autonomous completion of certain jobs devoid of human intervention. Additionally, a notable paradigm shift exists wherein job tasks necessitating independent execution can now harness GPT assistance, thereby markedly enhancing overall work efficiency (Rafner et al., 2023). Simultaneously, unforeseen events, such as emergencies, have the potential to instigate the creation of novel job roles and the transformation of existing ones, thereby fostering job evolution. A case in point is the post-COVID-19 landscape, where hybrid working has become predominant, imposing heightened demands on the proficient operation of digital tools in the workplace. For instance, the integration of cameras to document experiments facilitates the capture and sharing of specific details with trainers or trainees during scientific endeavors (Erika et al., 2022). Consequently, there is an exigent need to expeditiously model the mechanisms underpinning job evolution and discern plausible patterns of evolution. Such endeavors hold the promise of yielding manifold advantages in the face of an evolving employment landscape. For individuals, discerning insightful patterns in job evolution holds the potential to inform proactive career development, enabling the establishment of accurate learning objectives for career training (Santilli et al., 2019). Concerning organizations, the identification of job evolutionary mechanisms serves to streamline the job redesign and optimization process, thereby enhancing organizational efficiency (Cohen and Mahabadi, 2022). Ultimately, at the labor market level, the discernment of job evolutionary mechanisms constitutes a crucial framework for sustaining market equilibrium between supply and demand, fostering sustainable development.

In the literature, distinct research categories emerge. The initial set of studies primarily delves into macro shifts within the labor market. However, these studies predominantly scrutinize the impact of isolated factors, such as the development of AI technology or the occurrence of emergency events, on labor market changes (Långstedt et al., 2023, Ng et al., 2021, Sunley et al., 2020). This approach struggles to unveil job evolutionary patterns amid diverse external environmental shifts. The second cluster of studies concentrates on organizational science, delineating the vertical movement of individuals within established organizational structures (Cohen and Mahabadi, 2022). Yet, given technological advancements and the growing interconnectivity of industries, a more comprehensive perspective examining job evolution mechanisms and patterns across the entire labor market is imperative. In terms of methodology, prevailing studies predominantly employ surveys or interviews to gauge influencing factors, posing challenges in promptly and efficiently discerning job evolutionary patterns from a quantitative standpoint. Additional detailed works on related studies have been consolidated in Supplementary Section 1.

To address this research void, we investigate job evolution through the lens of job reconfiguration, conceiving it as a complex system propelled by diverse organizations. Viewing a job as a fusion of knowledge, organizations articulate distinct job requirements for varying knowledge under disparate labor market conditions. Moreover, different jobs could yield distinct market values and costs. Using organizational knowledge creation behaviors from organizational science, we model the job evolution mechanism and construct a simulation model substantiated by extensive data validation, focusing on the reconfiguration of knowledge required within the job perspective. Figure 1a illustrates the conceptual evolution process driven by organizations' job postings and the ensuing knowledge alterations in the labor market. Outlined in Fig. 1b, the construction of an interpretable computational model for simulating a system that incorporates knowledge and concurrent job evolution involves four key steps.

Initially, in STEP 1, we established the world knowledge network and organizational knowledge set and devised interaction mechanisms between the organization and world knowledge. Within the realm of knowledge networks, nodes denote discrete units of knowledge, with the connections between these nodes, achieved through coupling or combination, harboring the potential to engender value (Carnabuci and Bruggeman, 2009, Yayavaram and Ahuja, 2008). We model the world knowledge relationships as a small-world network, which is characterized by high clustering within local areas of the network and short path lengths across the entire network (Watts and Strogatz, 1998). This mirrors how knowledge is organized and accessed in reality. In real-world knowledge systems, specialized knowledge tends to form tight clusters where closely related domains share strong interconnections. For instance, within a field like software engineering, knowledge of programming languages might be tightly linked to knowledge of algorithms and software architecture. However, innovations often occur when these clusters interact with more distant knowledge areas, which can be efficiently connected through short paths (Wei et al., 2020), another feature of small-world networks. AlphaFold exemplifies how breakthroughs occur when distant knowledge clusters—deep learning (DL) and protein structure prediction—are linked by a short path. The bridge between these clusters was sequential modeling, used in NLP to analyze word sequences. By treating proteins as amino acid sequences and applying DL techniques like attention mechanisms, researchers achieved a breakthrough in structure prediction, leading to AlphaFold's success. Empirical studies from various industries support the idea that real-world knowledge networks exhibit small-world properties. For example, research has demonstrated that both academic collaborations (Wallace et al., 2012) and industrial innovation networks (Schilling and Phelps, 2005) show the same high clustering and short path lengths found in small-world networks. By amalgamating the concept of organizational knowledge creation behaviors, we formulated four mechanisms encapsulating the dynamic knowledge creation behaviors network at the organizational level, elucidated in the forthcoming section.

In STEP 2, the interconnected nodes, facilitated by dynamic knowledge creation behaviors, empower organizations to traverse the knowledge network actively, seeking and integrating knowledge along the edges. Simultaneously, organizations can transfer a knowledge set among collaborators. Founded on this knowledge bedrock, organizations can rearrange or recycle internal knowledge. Through purposeful exploration and utilization of the knowledge network, organizations can innovate new job positions that harness diverse knowledge combinations to adapt to shifts in the labor market, ultimately culminating in value creation.

To validate our model, we conducted a rigorous analysis in STEP 3 utilizing long-term job posting data extracted from a prominent online recruitment platform in China. Our dataset encompasses a substantial number of job postings spanning from July 2014 to November 2020. To ensure privacy compliance for both users and platform operators, any identifiable information and sensitive commercial data within these job descriptions were either hashed or excluded. To manage the substantial volume of data effectively, we specifically selected job descriptions from the top 3600 companies with the highest frequency of job postings on

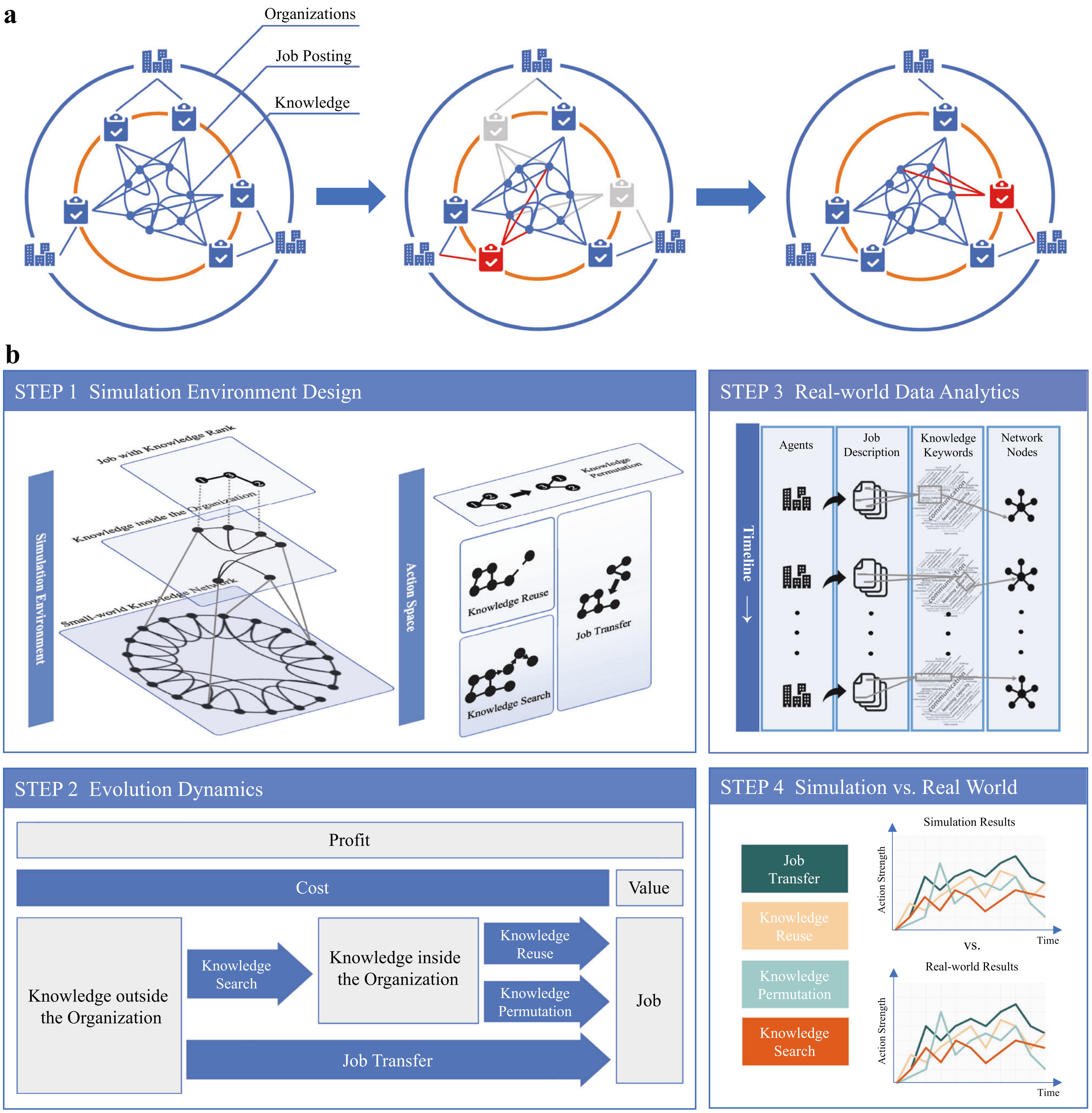

Fig. 1 Modeling job evolution from a knowledge creation perspective. a Organizations in the labor market disseminate job postings. Each job posting entails several knowledge requirements, and the collective knowledge needed for all positions forms a small-world network. The processes of job posting and knowledge acquisition for organizations are dynamically evolving. **b** Main steps of our research: STEP 1, Building simulation environment: global knowledge network with small-world traits, intra-organizational knowledge network, and job-specific knowledge subsets. Agent Action Space involves knowledge search, reuse, job transfer, and knowledge permutation. STEP 2, Designing agent dynamics: agent actions have unique costs, and jobs generate diverse values. Agent dynamics aims to maximize individual profit, defined as the difference between accrued values and costs. STEP 3, Doing a statistical analysis of authentic data: we consider enterprises as quasi-agents, while each job description represents a job. Skill-related keywords are extracted from these job descriptions and endowed with the role of knowledge nodes. STEP 4, Validating simulation effectiveness: comparative analysis with real-world data confirms simulation efficacy and conclusion accuracy for our model.

the platform, resulting in a comprehensive dataset comprising over 20 million job postings. Employing structured text processing techniques, we meticulously tagged each job posting with multiple skill keywords, totaling over 1 million skill-related keywords. This systematic structuring and analysis of textual content provide us with an insightful understanding of the evolving knowledge landscape demanded in the job market—a pivotal aspect of our investigation. Using these tags, we systematically tracked the temporal evolution of four distinct mechanisms governing job evolution. The calculation of mechanism strengths through evolution is elucidated in Supplementary Section 2. The statistical analysis of real-world data and the region/industry distributions of organizations on the Boss Zhipin platform can be found in Supplementary Section 3.

In STEP 4, the outcomes of our computational model, coupled with validation against real-world data, have unveiled noteworthy fluctuations in patterns and predominant modes of job evolution across various phases of organizational development. During the initial establishment of an organization, the predominant strategy involves swiftly building its knowledge base through external knowledge searches—comprising direct importation of jobs consisting entirely of new knowledge or emulating existing positions, constituting ~75% of all simulation samples. Upon achieving organizational stability, the frequency of directly importing job tasks decreases by ~50%. Subsequently, as the organization progresses, there is a gradual shift towards the reconfiguration of existing knowledge to generate entirely new positions. Initially, constrained by limited internal knowledge resources impeding Knowledge Use, the intensity of this restructuring is only a quarter or lower compared to Knowledge Search in the early stages of enterprise development. However, as the organization amasses a richer internal knowledge reservoir, the intensity of Knowledge Reuse surpasses that of Knowledge Search, reaching ~1.5 times its magnitude during the stable phase. Throughout the entire evolution process, fine-tuning the knowledge within existing positions remains notably significant. Regarding changes in the knowledge network during evolution, we observe a reduction of over 50% in knowledge utilization rates for 16% of the covered areas, with 2% experiencing a reduction of over 80%. Simultaneously, 20% of the knowledge utilization rates increase to 150% or more of their original values, indicating the diffusion of organizations' original knowledge. These results are further validated through supplementary real data analysis across different economic regions and industries in China, along with a discussion of potential biases from the Boss Zhipin platform (see Supplementary Sections 3 and 4). Furthermore, by manipulating essential parameters within our model, labor market characteristics can be adjusted. For example, controlling the valuable job rate (VJR) reveals an unexpected insight: a non-linear relationship exists between the pre-evolution valuable job proportion and job evolution intensity. This suggests that in areas where knowledge readily forms valuable jobs, there is an impediment to the job evolution process. In our case study, knowledge pieces with increased utilization are concentrated within jobs associated with an elevation in value. About 44% of the knowledge within jobs linked to an increase in value exhibits enhanced utilization rates (see Supplementary Section 7).

In essence, our examination of patterns, trends, and underlying mechanisms governing job evolution at a macroscopic scale yields valuable insights into the transformative processes of industries and professions. This scrutiny illuminates how skills and competencies adapt to address emergent demands. Employing a comprehensive analysis of large-scale labor market data and computational simulation, our objective is to furnish empirical evidence and insights into the dynamics of job evolution within knowledge networks. This endeavor contributes substantively to the theoretical comprehension of organizational dynamics.

Methods

Theoretical model. As illustrated in the above explanations about research progress, job evolution is investigated from a knowledge perspective in this paper. As documented in occupational coding systems such as O*NET (2024) and ESCO (2024), different jobs require the collaboration of different types of knowledge to accomplish the tasks associated with the job. Building upon this premise, we consider a job as an ordered assemblage of different knowledge nodes, symbolizing the involvement of a variety of distinct knowledge components necessary for completing that job. Furthermore, these knowledge points possess differing levels of importance within the context of that specific job, represented by the knowledge node rankings in the ordered assemblage. We considered four different job updating mechanisms. These mechanisms, namely Job Transfer, Knowledge Permutation, Knowledge Search, and Knowledge Reuse, exhibited distinct patterns over time. The four mechanisms are grounded in established theories and empirical findings from the fields of organization science, knowledge management, and innovation, reflecting real-world strategies that organizations use to adapt and evolve in dynamic environments.

Job Transfer is grounded in the theoretical framework of knowledge transfer across organizational boundaries (Easterby-Smith et al., 2008). Extensive empirical research has shown that organizations often acquire external knowledge and capabilities by transferring entire job tasks through mechanisms such as mergers, acquisitions, or team expansions. This process enables organizations to rapidly assimilate new competencies, integrating them into existing operations and facilitating diversification and expansion into new areas (Bennett and Feldman, 2017, Hernandez and Menon, 2018). Based on this, we abstract the mechanism of Job Transfer, wherein an organization acquires a comprehensive set of knowledge associated with a specific job directly from external sources. The organization can either apply the job tasks as they are or leverage the knowledge embedded within the job to accomplish new objectives.

Knowledge Search, on the other hand, is deeply rooted in the concept of knowledge exploration within organizational learning theory (Malone, 2002). Exploration involves the pursuit of new knowledge and innovation, often achieved through interactions with external sources. This mechanism is particularly critical in fast-moving industries where technological advancements necessitate continuous external engagement to maintain competitive advantage and foster innovation (Kneeland et al., 2020, Tortoriello et al., 2015). Typically, this is done through the recruitment of specialized talent in emerging fields. Consequently, Knowledge Search is defined as the process of seeking external knowledge networks to acquire novel expertise. The key difference between Knowledge Search and Job Transfer lies in their scope: while Job Transfer involves acquiring all knowledge embedded in a specific external job, Knowledge Search focuses on acquiring individual pieces of knowledge incrementally.

Knowledge Reuse is grounded in the theory that the ability to repurpose and recombine existing knowledge is a critical driver of both innovation and operational efficiency (Hsu and Lim, 2014). This mechanism allows organizations to exploit their accumulated knowledge, minimizing the need for constant external searches while fostering creativity. Empirical studies have shown that Knowledge Reuse often coincides with internal workforce transitions and role adjustments, enabling organizations to adapt to evolving business needs without acquiring entirely new capabilities (Berchicci et al., 2019). Accordingly, Knowledge Reuse is defined as the application of existing knowledge to new jobs.

Finally, Knowledge Permutation draws on empirical studies of job task optimization and the contextualization of knowledge within organizational processes (Denis et al., 2004). Through this mechanism, organizations can refine their job task execution strategies without necessarily incorporating new knowledge outside the job. This adaptability is crucial for organizations navigating incremental changes in their operational environments (Li et al., 2023). We define Knowledge Permutation as the process of adjusting the relative importance or weight of different knowledge components within a specific job.

The formal definitions of the four evolution mechanisms in both simulation and real-world data analysis are provided in Supplementary Section 2.

Operationalization. We define the knowledge network $G(V, E)$, where the set of nodes V represents different knowledge and the set of edges E represents the connections between knowledge elements. An organization's knowledge base can be viewed as a subgraph of the overall knowledge network (Yayavaram and Ahuja, 2008). Knowledge must be applied to specific jobs to create value (Waheed and Kaur, 2016). Therefore, job evolution can be defined as a multi-agent combinatorial optimization problem on the knowledge network: the organization, as the primary agent in job evolution, incurs a cost of C to acquire and combine knowledge, while different combinations of knowledge can accomplish specific jobs and create value ϕ. The organization's optimization objective is to maximize its value Ψ during the job evolution process, specifically maximizing $\Psi = \phi - C$.

Different combinations of knowledge can accomplish specific jobs and create value. To reduce computational complexity, we define jobs as subgraphs $G_i(V_i, E_i)$ on knowledge network G, where V_i represents the set of N distinct knowledge nodes and E_i represents the edges connecting these nodes, i.e., $E_i = \{e_{pq};\ p, q \in V_i\}$. The edges in the knowledge network correspond to cooperative relationships among knowledge elements during the value-creation process. Therefore, the distribution of job values (JV) should be related to the structure of the knowledge network. Specifically, jobs that are closer in distance on the knowledge network should have similar values.

We characterize the distance between different jobs using the average transition path length between two subgraphs. Let $G_1(V_1, E_1)$ and $G_2(V_2, E_2)$ be the two subgraphs, and $l_G(v)$ denotes the shortest distance from node v to the graph G. The average path length from G_1 to G_2 is defined as:

$$D(G_1 \rightarrow G_2) = \frac{1}{|V_2|} \sum_{v \in V_2} l_{G_1}(v). \tag{1}$$

It is important to note that this path length definition is asymmetrical, i.e., $D(G_1 \rightarrow G_2) \neq D(G_2 \rightarrow G_1)$. This definition offers several advantages:

- If G_1 is a subgraph of G_2, then $D(G_2 \rightarrow G_1) = 0$ and $D(G_1 \rightarrow G_2) \neq 0$, which aligns with the characteristic of downward compatibility between different jobs.
- By using the average shortest distance of each node, the influence of a few distant nodes on the overall distance between two jobs is minimized.
- It effectively handles the distance between jobs in different domains. The introduction of the shortest distance $l_G(v)$ ensures that cross-domain jobs and non-cross jobs within multiple knowledge domains they cover have short distances.

Based on this, the symmetric distance between jobs G_1 and G_2 is defined as:

$$D_G(G_1, G_2) = \frac{D(G_2 \rightarrow G_1) + D(G_1 \rightarrow G_2)}{2}. \tag{2}$$

The relevance of knowledge components to a job influences JV. This assumption is grounded in the concept of contextual knowledge quality (Kyoon Yoo et al., 2011), which emphasizes the alignment of specific knowledge with the requirements of a particular job. To represent knowledge relevance, we order the knowledge components within jobs (Lee, 2005). For a job with N distinct knowledge components, there are $N!$ possible permutations of these components, each representing a unique sub-job. To evaluate the value of these sub-jobs, we utilize the closeness centrality (Wang et al., 2014) of each node within the network of knowledge contributing to the job. Closeness centrality, which measures a node's accessibility, serves as a valid proxy for relevance because it reflects how easily related knowledge can be integrated and applied within the job's context. This metric highlights the contextual importance of knowledge in meeting job-specific requirements.

Let $l_w(v)$ denote the shortest path length between nodes v and w in the graph. For job G_i, the closeness centrality of a knowledge component $v \in G_i$ is defined as:

$$\xi_{G_i}(v) = \frac{1}{\sum_{w \in G_i} l_v(w)}. \tag{3}$$

Knowledge components with higher closeness centrality are considered to have higher contextual quality within the job, thus contributing greater knowledge weight to maximize the job's value (Kotlarsky et al., 2014). The value of a sub-job, represented by the ordered knowledge components $\tilde{G}_i = (v_1^i, v_2^i, \ldots, v_N^i)$, can be calculated as:

$$\phi(\tilde{G}_i) = \phi(G_i) \frac{\sum_{n=1}^{N} (N + 1 - n) \xi_{G_i}(v_n^i)}{\sum_{n=1}^{N} \xi_{G_i}(v_n^i)}. \tag{4}$$

To enhance the value of sub-jobs, key knowledge components that are highly concentrated within the job should be assigned greater weights. Similarly, for cross-domain jobs, knowledge components that act as "bridges" should also receive higher weights.

The acquisition of new knowledge by organizations incurs a cost C, which can be decomposed into knowledge search cost C_{search}, knowledge coupling cost $C_{coupling}$, competition cost $C_{competition}$, and job transfer cost $C_{transfer}$, as follows:

$$C = C_{search} + C_{coupling} + C_{competition} + C_{transfer}. \tag{5}$$

- Knowledge Search Cost: the existence of knowledge boundaries incurs knowledge search costs (Levina and Vaast, 2005). Knowledge search cost is influenced by an organization's existing knowledge and the structure of the knowledge network. Let G_m represent the subgraph formed by an organization's existing knowledge in the knowledge network G. The cost of searching for new knowledge v is defined as:

$$C_{search} = l_{G_m}(v). \tag{6}$$

- Knowledge Coupling Cost. When newly acquired knowledge is integrated into an organization's existing knowledge network, coupling costs arise (Chiu et al., 2006). The coupling cost is defined as the characteristic path length of a new job G_i.

$$C_{coupling} = \frac{N-1}{N} \sum_{u \neq v \in G_i} l_u(v). \tag{7}$$

- Competition Cost: the pursuit of the same knowledge by multiple companies in a system incurs competition costs. The competition cost can be defined as the number of companies in the system that already possess the knowledge.

$$C_{competition} = \sum_m \mathbb{I}(v \in G_m). \tag{8}$$

- Job Transfer Cost: an organization can acquire all the knowledge in a job $\tilde{G}_i$ from another organization through job transfer. The job transfer cost for an organization depends on the importance of $\tilde{G}_i$ in the other organization. It is defined as the proportion of the value of $\tilde{G}_i$ to the total value of all jobs S_n in that organization, multiplied by the search cost.

$$C_{transfer} = \frac{\phi(\tilde{G}_i)}{\sum_{\tilde{G}_j \in S_n} \phi(\tilde{G}_j)} (1 + C_{search}). \tag{9}$$

- Knowledge Supply: the supply of knowledge in the market is limited (Hasan et al., 2015). Let K denote the total capacity of a knowledge element. The utilization of knowledge consumes the corresponding capacity based on the knowledge weight. Higher-weight knowledge components consume more capacity. This limitation can be perceived as the cost of knowledge application, preventing organizations from infinitely utilizing a specific knowledge element to complete jobs.

The driving force behind the system's evolution is the pursuit of maximum benefits Ψ by organizations. At time t, the behavior of the organization must satisfy the objective of maximizing $\Psi_t - \Psi_{t-1}$. To control computational complexity in the simulation process, we have imposed a constraint that all jobs require a fixed knowledge quantity N. Within a simulation step, organizations can sequentially perform zero to three of the following actions:

- Obtain a new job from another organization (Job Transfer).
- Modify the weighting of existing knowledge in a current job (Knowledge Permutation).
- Search for new knowledge from outside network (Knowledge Search) or reuse knowledge from its own knowledge base (Knowledge Reuse), replace an old piece of knowledge in a job being executed, and enable the accomplishment of the new job.

The details of the simulation algorithm are described in Supplementary Section 5.

Results

Main results. We utilize two primary indicators to unveil patterns in job evolution. The first indicator focuses on the action proportion of the four job evolution mechanisms, calculated as the count of agents engaging in a particular mechanism at a single time step divided by the total number of agents. Since all job evolution occurs within these four mechanisms, this indicator serves as a comprehensive representation of both the overall evolution intensity and the fine-grained structure of the evolution process. The second indicator scrutinizes the changes in knowledge utilization pre- and post-evolution. In terms of knowledge management, a pivotal aspect of job evolution lies in how the knowledge composition of jobs changes and how organizations explore and employ previously undiscovered segments within the knowledge network. To capture this, we employ a heat map to demonstrate the changes in the utilization of each knowledge node in the simulation, both before and after the evolution. This visualization method provides a clearer depiction of the alterations in knowledge node usage, enhancing our understanding of how organizations uncover and harness untapped segments of the knowledge network during the evolution process.

In the observed dynamics of the four mechanisms within the evolutionary process, several noteworthy trends emerge (see Fig. 2a), shedding light on the intricate ways in which enterprises adapt and optimize their knowledge resources. These observations are instrumental in understanding the strategies employed by enterprises throughout their lifecycle, from inception to maturity. Notably, our simulation results exhibit a remarkable alignment with real-world data, demonstrating a close fit in terms of both the relative strengths and trends of these four evolutionary mechanisms. This alignment underscores the robustness of our computational model and its ability to capture the intricate dynamics of real-world workforce evolution.

In the early stages of an enterprise's establishment, Job Transfer plays a critical role, accounting for ~40% of the overall activity. This high intensity reflects the survival strategy of emerging companies, which rely heavily on external knowledge to fill critical capability gaps (Dencker et al., 2009). By acquiring entire teams or specialized knowledge units from more mature industry players, new companies can rapidly enter new markets or domains, leveraging the expertise of established actors. This is commonly seen in real-world practices such as strategic acquisitions or high-profile hiring campaigns (Groysberg and Lee, 2009). However, as enterprises grow and stabilize, the intensity of Job Transfer diminishes significantly, dropping below 20% in the later stages. This decrease signals a shift from rapid expansion to a focus on operational refinement (Davies and Brady, 2000), where mature organizations rely less on external acquisitions and more on optimizing internal resources.

The interaction between Knowledge Search and Knowledge Reuse further illustrates the evolving balance between external and internal knowledge strategies. In the early stages of an enterprise's lifecycle, due to the limited internal knowledge available, the intensity of Knowledge Reuse is only about a quarter—or even less—compared to Knowledge Search. However, as enterprises build a more robust internal knowledge base, Knowledge Reuse gradually takes precedence. By the later stages of development, Knowledge Reuse surpasses Knowledge Search, reaching ~1.5 times the intensity of the latter during stable phases. This shift reflects the organization's increasing capacity to repurpose and optimize its existing knowledge base (Benson and Rissing, 2020). This cycle—from external acquisition to internal accumulation—resonates with the framework proposed in (Cassiman and Veugelers, 2006), where external and internal knowledge acquisition mechanisms are seen as complementary forces.

Knowledge Permutation maintains a consistently high intensity throughout the observed evolutionary process, which reflects its critical role in allowing enterprises to continuously fine-tune the knowledge composition within jobs. This persistent activity highlights the enterprise's need to align its internal operations with both evolving internal requirements and the dynamic external environment. In the real world, this mechanism is particularly valuable in enabling organizations to adapt to segmented market demands (Nair and Boulton, 2008, Randhawa et al., 2021). As businesses operate across diverse markets with varying customer needs, they often need to adjust the weighting and prioritization of existing knowledge components to cater to specific niche requirements without overhauling their entire knowledge base. For example, a company serving multiple geographic regions or product lines may need to optimize its internal knowledge structures differently depending on the market it is targeting. Knowledge Permutation allows the company to flexibly reconfigure the same set of skills and knowledge, ensuring it can meet the nuanced demands of different market segments.

Our correlation analysis further reveals the interrelationships among these mechanisms. The Pearson correlation coefficient between Knowledge Permutation and Knowledge Search is the highest, at 0.98, indicating a strong link between these processes. The second highest correlation is between Knowledge Permutation and Knowledge Reuse, at 0.60. These imply that organizations, after acquiring new knowledge or reusing existing resources, often need to adjust the relative weights of knowledge components within jobs to make space for these newly integrated, high-value elements, ensuring they contribute effectively. In contrast, Knowledge Reuse and Knowledge Search show the lowest correlation at 0.46, underscoring their complementary nature as organizations balance external knowledge acquisition with the internal optimization of resources.

In conclusion, the dynamics of these knowledge utilization mechanisms provide valuable insights into the strategies employed by enterprises across different lifecycle stages. The observed trends underscore the importance of flexibility and adaptability in managing knowledge resources, both internal and external. These findings offer critical insights for enterprises

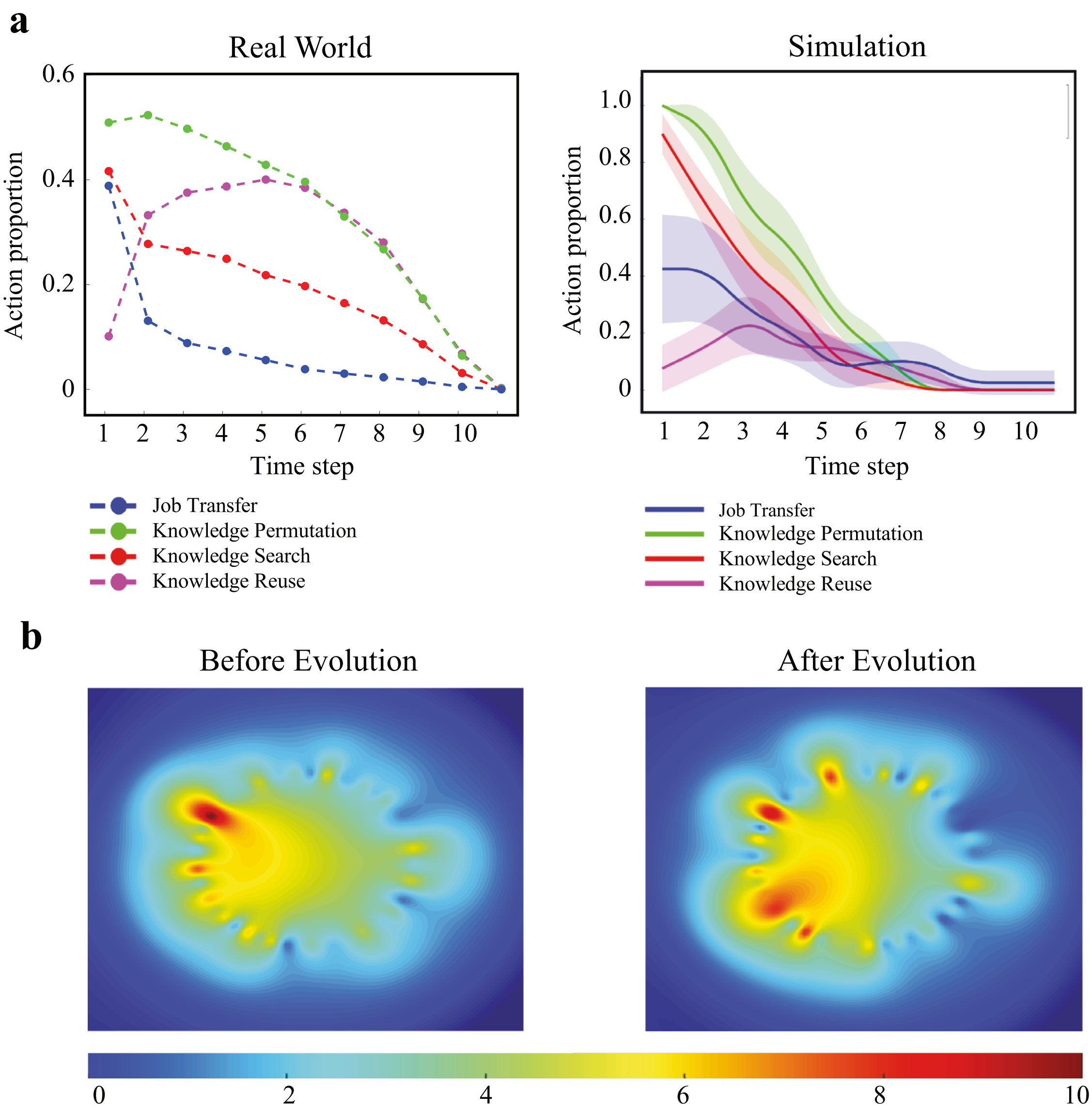

Fig. 2 Main results of our research. a The intensity variation of four job evolution mechanisms over time in the real dataset and the simulation process. The horizontal axis represents the time, while the vertical axis represents the proportion of agents adopting each evolution mode within the time step, out of the total number of agents. Real-world results: the dotted line represents the mean value across the active enterprises. Simulation results: the solid line represents the mean value across five simulations, and the shaded region represents one standard deviation above and below the mean. **b** The changes in knowledge utilization intensity before and after the simulation. Knowledge nodes are distributed according to their positions in the knowledge network (closer nodes in the graph represent closer positions in the network). The colors represent the average knowledge utilization intensity across five simulations.

seeking to thrive in today's dynamic business landscape and pave the way for further exploration into the factors driving these observed trends.

The visualization of knowledge usage by organizations before and after the simulation in Fig. 2b reveals significant trends that align with real-world job evolution. Initially, the red-highlighted areas, representing possessed and utilized knowledge, are concentrated in specific regions, indicating the organization's focus on a limited set of knowledge areas. However, as the evolutionary process unfolds, companies actively search for new knowledge and expand their capabilities, resulting in a more widespread distribution of utilized knowledge. More precisely, 20% of the knowledge utilization rates increase to 150% or more of their original values. This expansion reflects knowledge diversification, where the organization's knowledge base broadens as it absorbs new knowledge from previously untapped domains. Instead of merely redistributing existing resources, companies integrate knowledge from other fields, expanding the breadth of their expertise (Kabir, 2019). This mirrors real-world practices, where organizations actively seek to diversify their knowledge base by incorporating insights and skills from external sources, allowing them to adapt to a wider range of challenges and opportunities (Kaur, 2022). Simultaneously, the disappearance of certain knowledge areas, as evidenced by the transition from red to blue, highlights the process of discarding outdated knowledge. Specifically, there is a reduction of over 50% in knowledge utilization rates for 16% of the areas, while 2% exhibit a reduction of over 80%. In the real world, as industries and technologies evolve, companies must continuously reassess their knowledge assets, phasing out knowledge that is no longer relevant or valuable (Nujen et al., 2018). This reduction in knowledge utilization demonstrates how organizations shed obsolete knowledge to make room for more relevant, updated capabilities.

Influence of parameters. We delved into exploring the impact of various simulation parameters on the process of position evolution. In our initial research phase, particular attention was devoted to scrutinizing the influence of the VJR. This parameter signifies the proportion of jobs possessing positive values within the complete set of knowledge node combinations. Our findings showed important trends (see Fig. 3). At a low valuable job proportion (1%), job evolution quickly ceased, with lower frequencies observed for all updating mechanisms and inconspicuous changes in knowledge utilization. However, at a moderate proportion (10%), we observed significantly higher frequencies on all four mechanisms and more intense knowledge utilization changes compared to a relatively high proportion (20%). These results demonstrate a non-linear relationship between valuable job proportion and job evolution. The empirical analysis of real-world data further corroborates the findings presented here. In the later stable stage of enterprise development, the ratio of execution intensities for the four job evolution mechanisms under small VJR, medium VJR, and large VJR conditions is ~1:3:2. The reasons are as follows. A very low VJR implies a challenging task of identifying and locating valuable jobs, thus impeding the evolution process. Conversely, the similar muted activity in the scenario with a substantially high proportion stems from an entirely different rationale. A high VJR makes it notably effortless for agents to identify and access knowledge, enabling the execution of easily found valuable jobs with minimal effort. They do not need to conduct multiple actions sequentially to fulfill a specific hard-to-find valuable job. Instead, they can promptly fulfill numerous straightforward valuable jobs with fewer and simpler actions. In conclusion, the underlying reality behind the seemingly silent with very high VJR lies in the ease for each agent to attain their evolution targets.

In the business realm, entities facing elimination often demonstrate very low VJR, making the creation of new values nearly unfeasible. Consequently, limited job evolution transpires in such scenarios. Administrative departments in enterprises typically exhibit a notably high VJR, considering those crucial skills in such areas, such as communication and organizational aptitudes, are highly transferable and shareable. Therefore, fewer job changes are needed here because the original settings are enough for new scenarios. In contrast, high-technology departments reside within an environment showcasing moderate VJR. These departments necessitate a delicate amalgamation of skills to generate value, compelling enterprises to actively engage in trial-and-error approaches to fulfill these requisites. Hence, in high-technology departments, the turnover rate among employees is notably higher compared to administrative departments (Chien and Chen, 2007, Lin, 2020). These findings offer invaluable insights into the intricacies of position evolution concerning the valuable job proportion.

In the second phase of our study, we investigated the impact of other parameters on the evolution of positions (Fig. 4).

First, our findings indicate that a higher number of initial jobs (INJ) within an organization leads to a more diverse and enriched evolution process. This pattern is particularly relevant for early-stage startups, where engaging in multiple job tasks allows for greater experimentation and exploration (Priyono and Hidayat, 2022). In the real world, more jobs mean broader knowledge coverage, which enhances innovation by enabling diverse combinations of existing knowledge. This increased diversity helps organizations identify the most promising growth paths, improving adaptability in a dynamic market (Ghezzi and Cavallo, 2020). Besides, in the initial stages, a higher number of INJ fostered more extensive knowledge reuse. This increase in

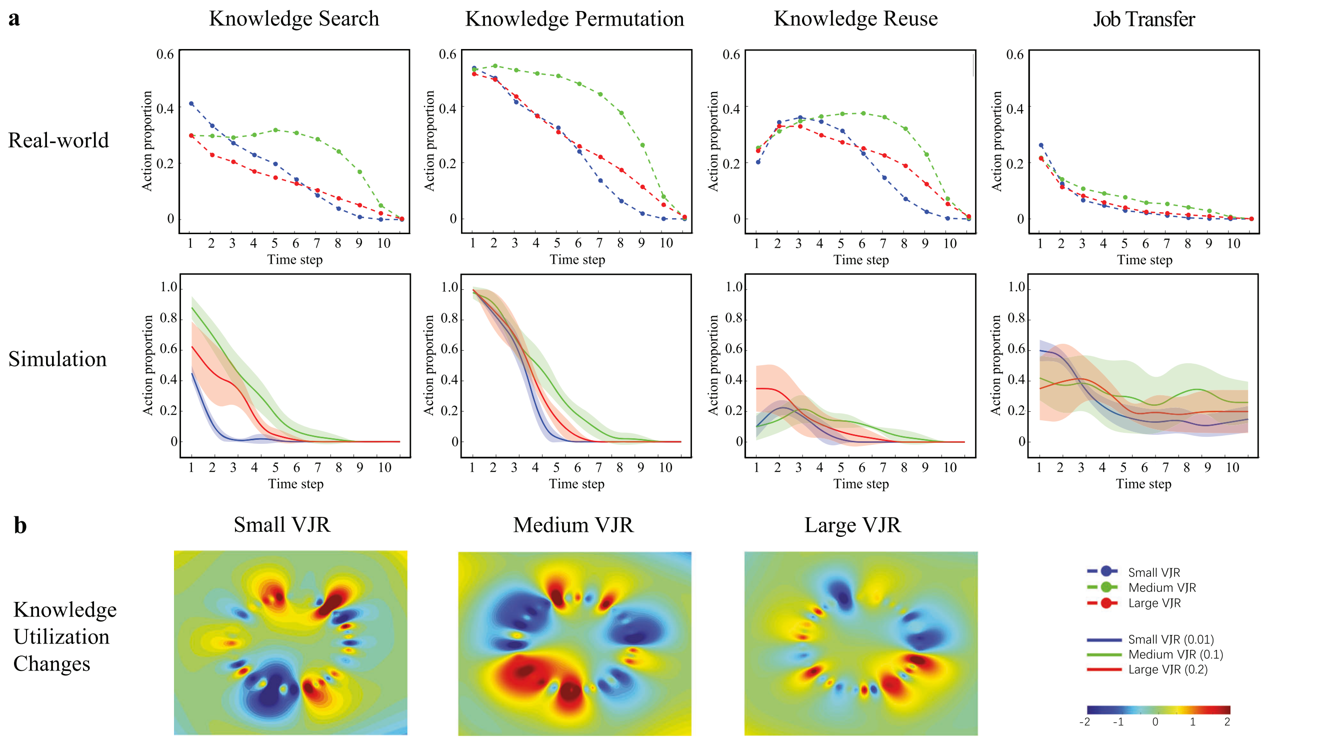

Fig. 3 Comparing simulation results across varying valuable job rates (VJR). a Real-world results: the dashed line represents the mean value derived from an active enterprise pool of 1800. Simulation results: the solid line signifies the mean value from five simulations, while the shaded region encapsulates one standard deviation above and below the mean. **b** Knowledge usage alterations: knowledge nodes are positioned relative to their network locations, where closer nodes in the graph denote network proximity. A color spectrum is employed here to vividly portray the average knowledge utilization intensity changes observed across five simulations.

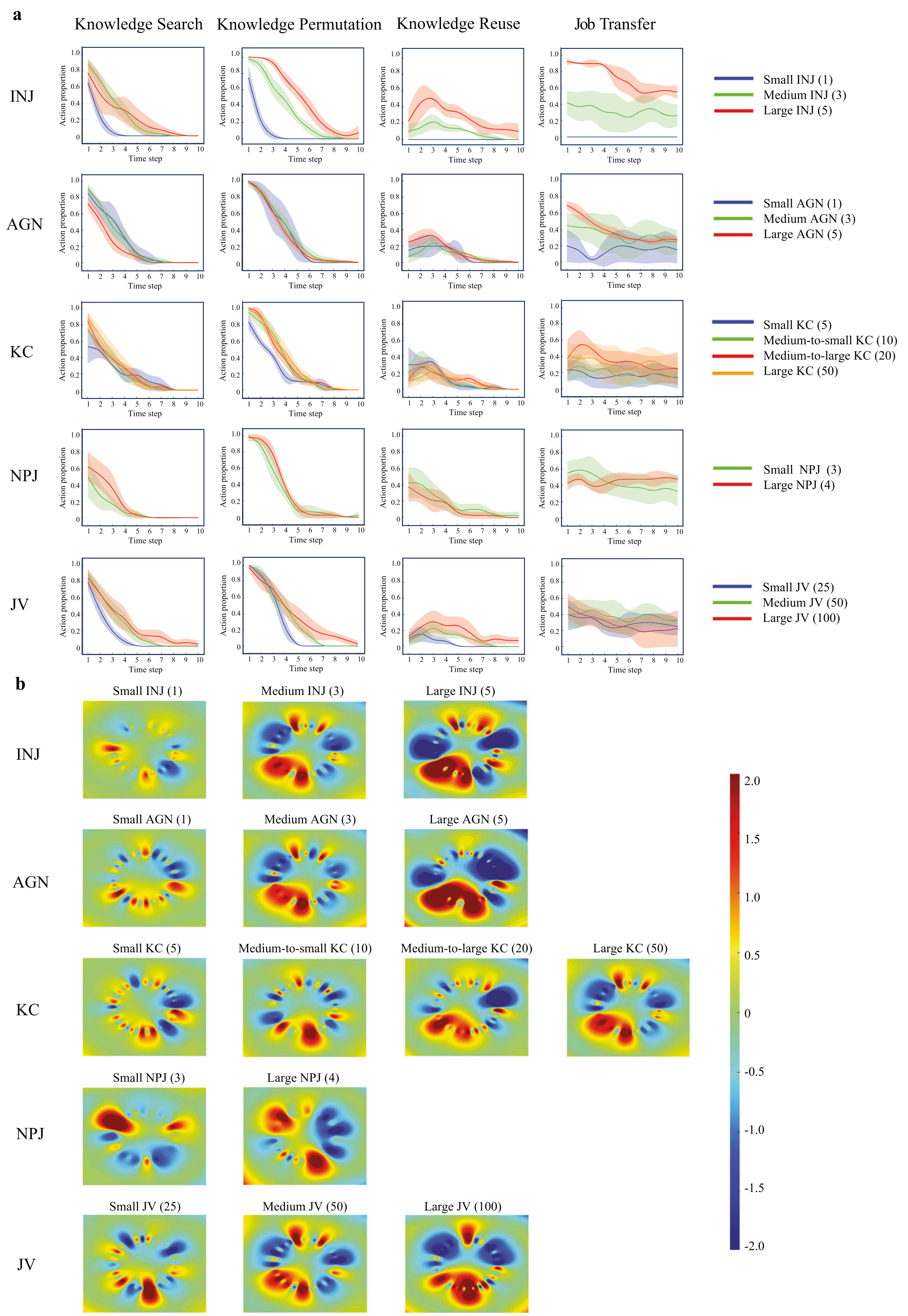

Fig. 4 Comparing simulation results across varying variables. a Comparison of the intensity of four career evolution mechanisms under different simulation parameters, INJ, AGN, KC, NPJ, and JV. Solid lines represent the means of five simulation runs, and shaded regions depict the range within one standard deviation of the mean. **b** The differences in knowledge utilization intensity before and after the simulation. Knowledge nodes are spatially distributed in alignment with their respective positions within the knowledge network, with closer nodes in the graph signifying proximity within the network. The spectrum of colors employed here serves to illustrate the average knowledge utilization intensity changes across five simulations.

knowledge reuse came at the expense of knowledge search, as the system could only choose to prioritize either search or reuse at any given time.

Then, we investigated the influence of both the number of agents (AGN) and knowledge capacity (KC) on position evolution. Expanding the number of agents intensified knowledge competition, leading to higher usage costs. Similarly, reducing knowledge capacity suppresses job transfer, knowledge permutation, and knowledge search, particularly in the early stages of evolution. In both cases, the heightened competition for limited knowledge resources shifted the focus toward knowledge reuse as a more viable strategy. This mirrors real-world scenarios where organizations, faced with resource constraints and increasing competition for the same knowledge and talent, must rely more on optimizing existing knowledge rather than investing in expensive external searches. As knowledge becomes scarcer or more costly to acquire, organizations focus on internal exploration and reuse of available knowledge, allowing them to remain efficient in highly competitive environments (Hang and Zhang, 2024). These results underscore the trade-off between external knowledge acquisition and internal knowledge exploitation, highlighting the importance of managing knowledge capacity and competition to balance innovation with efficiency in the job evolution process (Zhou and Li, 2012). While our findings highlight the importance of internal Knowledge Reuse as a strategy for addressing knowledge competition, it is worth noting that external mechanisms, such as outsourcing and strategic alliances, also play a critical role in real-world scenarios (Gaimon and Ramachandran, 2021). Both mechanisms can be viewed as forms of external Knowledge Reuse, where organizations repurpose and integrate knowledge from external partners to complement their internal capacities.

The next part of our study focused on examining the influence of the knowledge quantity required for a single job (NPJ) on position evolution. We found that jobs with higher knowledge demand stimulated knowledge search from external sources while simultaneously suppressing knowledge reuse. The increased knowledge requirements compelled organizations to actively seek and acquire new knowledge externally to fulfill job demands, limiting the reliance on existing knowledge within the system. This is exactly what happens when companies in cutting-edge technology or high-complexity industries need to recruit experts or purchase new technologies to complete specific job tasks in the real world (Miles et al., 1995). Further analysis demonstrated that the effect of knowledge quantity on position evolution was contingent on the stage of the process. In the initial stages, jobs with a higher knowledge quantity necessitated a greater searching part of transfer costs, thereby hindering job transfer. However, as the evolution progressed, the organization accumulated a greater pool of knowledge, reducing the searching part of transfer costs associated with jobs requiring higher knowledge quantities. The changing costs of job transfer throughout evolution further underscore the significance of knowledge accumulation and its impact on resource allocation within organizations.

Finally, we examine the influence of JV on our simulation outcomes. At each time step, the simulated agents calculate the profit of each potential action by subtracting the action costs from the values of the newly created jobs. Without losing generality, we can vary one while keeping the other constant, as an increase in JV is effectively equivalent to a decrease in costs. For this analysis, we chose to vary the values of jobs. Specifically, we set the mean JV to 25, 50, and 100, respectively, while maintaining the relative order of different jobs unchanged. The results indicate that a lower JV results in a decreased intensity of Knowledge Search, Permutation, and Reuse. Additionally, it leads to a quicker stabilization (i.e., cessation of evolution) and reduced changes in knowledge utilization. This occurs because lower JV result in fewer profitable actions, thereby discouraging organizations from engaging in evolution mechanisms. The phenomenon aligns well with the real world, where low-profit firms tend to grow at a slower pace compared to high-profit ones. (Davidsson et al., 2009).

Recommendations based on our findings. The findings of this study highlight several important implications for individuals, organizations, and policymakers in managing knowledge and fostering job evolution. Early-stage companies, where job transfer plays a critical role, can benefit from strategies such as mergers, acquisitions, and strategic hiring to quickly acquire external knowledge and fill capability gaps. This approach is particularly effective when entering new markets or expanding operations. For individuals seeking rapid career growth and skill acquisition, joining such high-growth companies or startups offers a unique opportunity to gain experience quickly. As organizations mature, the emphasis shifts toward knowledge reuse, where optimizing internal resources becomes more important than seeking new knowledge externally. Investing in knowledge management systems, creating knowledge repositories, and promoting internal knowledge sharing can enhance innovation efficiency and reduce external dependence. Firms should also regularly update their knowledge bases to remove outdated information and ensure relevance. As organizations accumulate knowledge, the costs associated with knowledge search and reuse decrease, making job roles more adaptable and diverse. As a result, for individuals looking to innovate across domains, joining more established companies may offer the flexibility to experiment with more cross-disciplinary knowledge.

In fast-paced industries, such as AI, where technological advancements occur rapidly, knowledge search is essential for maintaining competitiveness. Besides, for jobs with high knowledge demands (high NPJ), companies increasingly rely on external expertise to meet their needs. For individuals in these sectors, it is critical to regularly assess and update their skill sets. Engaging in industry events, technology forums, academic journals, and online communities can provide a way to stay current with the latest trends and advancements. Companies operating in these sectors should establish strong external collaboration networks, recruit high-level talent, and leverage partnerships or outsourcing to continuously acquire cutting-edge knowledge.

Additionally, in departments with low VJR, such as administrative roles where job evolution tends to stagnate, organizations can explore skill transfer or redefine job roles to stimulate employee engagement in higher-value jobs. For individuals in these environments, it is crucial to proactively seek opportunities for internal mobility or cross-departmental collaboration to enhance their skill set. By proposing new job tasks or project ideas, employees can help their department discover more valuable work directions and avoid stagnation in roles with limited innovation potential.

From a policy perspective, governments have a key role to play in supporting these knowledge management strategies. On the one hand, policymakers should strengthen the alignment between higher education and high-tech industries to ensure a sufficient supply of skilled labor. By investing in education and training programs that focus on high-skill professions, governments can shorten the time it takes for companies to acquire necessary external knowledge and promote a more efficient balance between the supply and demand of specialized talent. On the other hand, policymakers should establish knowledge-sharing platforms and public initiatives that foster industry collaboration, enabling businesses to access external knowledge resources more easily. By offering R&D subsidies, setting up public innovation labs, and organizing technology exchange forums, policymakers can reduce barriers to knowledge acquisition and ensure that companies are well-positioned to navigate fast-changing industries. This coordinated effort between individuals, businesses, and policymakers can enhance adaptability and innovation across firms, while also improving the overall competitiveness of the labor market.

Robustness tests. During the simulation, it was challenging to precisely determine the type (random network, small-world network, or regular network, defined by the edge rewiring probability) and parameters (such as the number of nodes and node degrees) of the knowledge network. Despite this uncertainty, the model exhibited consistent and predictable behavior across different variations of these parameters. This consistency suggests that the model's performance is not heavily dependent on specific parameter values, indicating robustness in the face of parameter uncertainties. Additionally, our simulation assumes that organizations always choose the current optimal action at each time step. In reality, it is nearly impossible for organizations to evaluate every possible action and consistently select the best one. To address this, we incorporated an element of randomness into the decision-making process in our robustness tests. Specifically, at each time step, we identified the top 50 actions with the highest potential profit and randomly selected one as the final decision. The simulation results indicate that even under these sub-optimal conditions, the main patterns and trends still hold, further demonstrating the model's robustness to different decision processes.

In detail, we conducted simulations under different network parameters (Fig. 5a: fewer adjacent nodes; Fig. 5b: more adjacent nodes; Fig. 5c: smaller network), network types (Fig. 5d: random network; Fig. 5e: regular network), and organizational strategies (Fig. 5f: sub-optimal decision process). It is also important to note that JV and evolution costs are inherently linked to the network structure (see the "Methods" section for details). Consequently, changes in network types and parameters directly impact these values. As a result, when we adjust network types and parameters as part of our robustness tests, both JV and evolution costs vary accordingly. This implies that our tests on different network parameters also serve as indirect validations of how various JV and evolution cost functions influence the simulation outcomes.

When examining the four career updating strategies, we observed stable or predictable trends over time. Knowledge Permutation and Knowledge Search both exhibited a decreasing trend, with Knowledge Permutation having a higher proportion. This suggests that the model is robust in maintaining a gradual decrease in these strategies, regardless of the specific parameter values and decision processes. Furthermore, Knowledge Reuse showed an increase followed by a decrease or stability before decreasing. This pattern aligns with the underlying assumption that a certain quantity of prior knowledge is necessary for reuse. The consistency of this behavior across different variations indicates the model's robustness in capturing the dynamics of knowledge reuse.

In most experiments, Job Transfer exhibits a consistent initial high intensity, followed by a rapid decline in strength. However, under higher node degree settings, Job Transfer maintains stability in intensity throughout the simulation (see Fig. 5b). This phenomenon might be attributed to a reduction in the average distance between jobs due to a higher number of neighboring nodes. This reduction likely lowers the costs incurred by enterprises during the Job Transfer process, thereby facilitating and promoting the process of job transfer. Additionally, the

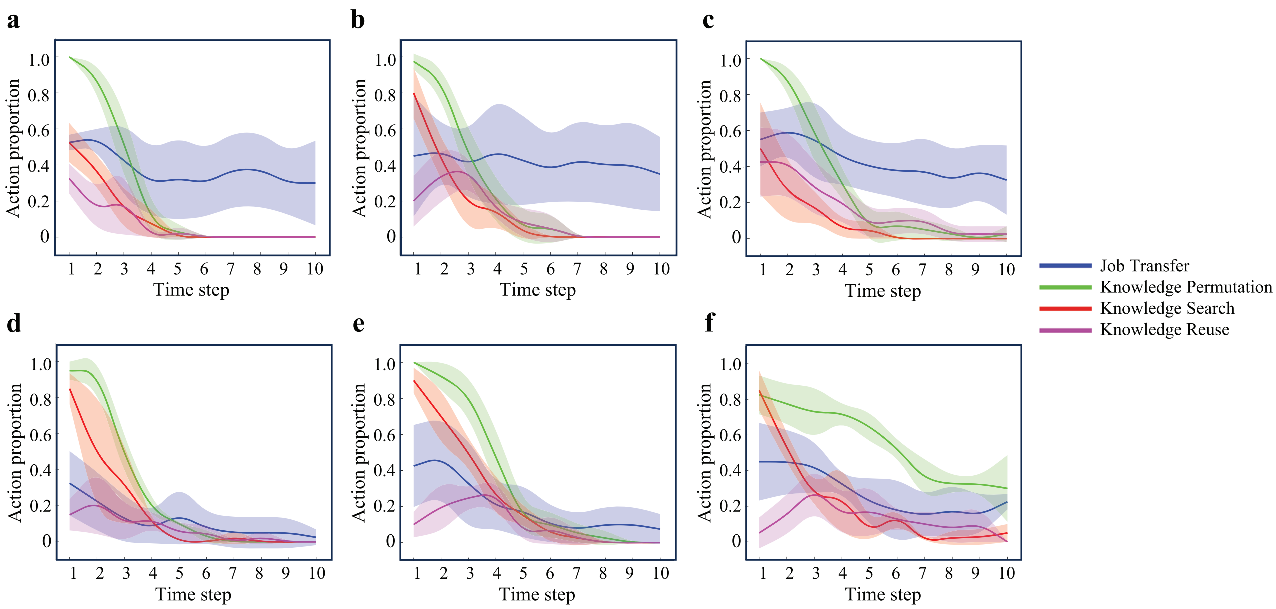

Fig. 5 Robustness analysis under different simulation parameters and decision processes against the main results. a Lower number of adjacent knowledge nodes (number of nodes = 50, node degrees = 3, edge rewiring probabilities = 0.1). **b** Higher number of adjacent knowledge nodes (number of nodes = 50, node degrees = 7, edge rewiring probabilities = 0.1). **c** Lower total number of knowledge nodes (number of nodes = 30, node degrees = 5, edge rewiring probabilities = 0.1). **d** Higher rewiring probability, leaning towards a random network (number of nodes = 50, node degrees = 5, edge rewiring probabilities = 0.2). **e** Lower rewiring probability, leaning towards a regular network (number of nodes = 50, node degrees = 5, edge rewiring probabilities = 0.01). **f** Introducing randomness into the decision process (randomly selecting one of the top 50 most profitable actions). The horizontal axis represents the simulation duration, while the vertical axis represents the proportion of agents adopting each evolution mode within the simulation step, out of the total number of agents. The solid line represents the mean value across five simulations, and the shaded region represents one standard deviation above and below the mean.

descent rate of all four mechanisms is slower in the sub-optimal decision settings compared to the optimal ones (see Fig. 5f). This is because, in the sub-optimal settings with added randomness, organizations require more steps to explore the action space and eventually reach the same stage that the optimal settings can achieve directly.

Discussions

This paper introduces an explainable multi-agent-based simulation approach aimed at deciphering the intricacies of job evolution from a knowledge management perspective. Two pivotal aspects significantly contribute to the effectiveness and simplicity of this model. The initial key aspect revolves around the creation of a distinct knowledge network serving as the foundational environment for all simulation processes. Our construction involves situating all knowledge within a small-world network, a structure well-documented for its typical role in cooperative value-creation processes. Jobs are constructed based on the network's nodes, prompting agents to navigate and execute actions within this network. The values and costs that propel agent dynamics stem directly from the network's structural configuration as well. This unification amalgamates nearly all the necessary properties essential for our simulation of the labor market into a singular network model, bestowing significant simplicity and interpretability upon our research work. The second focal point involves the proposition of four distinct mechanisms: Knowledge Search, Knowledge Permutation, Knowledge Reuse, and Job Transfer. These mechanisms serve as the foundational components that disassemble the opaque job evolution process into more discernible structural elements. This deconstruction allows for an in-depth exploration of the nuanced effects of various environmental parameters on the evolution process. Notably, each of these four mechanisms aligns with clear real-world data indicators, rendering our work both verifiable and applicable for practical comprehension in real-world scenarios.

Utilizing the model allows us to observe the unfolding of the four evolution mechanisms as each agent progresses through time. We have discerned significant fluctuations in patterns and prominent ways of job evolution at distinct phases in the development of organizations. These findings offer valuable insights into the behavioral tendencies adopted by companies when instigating and modifying jobs. Furthermore, the labor market characteristics can be altered by manipulating the values of pertinent parameters within the knowledge network. Consequently, we gain a visual representation of how diverse labor market attributes may influence the dynamics of the four mechanisms, consequently shaping the entire job evolution process in counterfactual experiments where variables are controlled. These controlled experiments enable us to acquire a more profound comprehension of the fundamental mechanisms governing job evolution. Moreover, we engage in regression analysis encompassing multiple simulation results (see Supplementary Section 6), presenting an avenue to explore the impact of nearly all variables on the evolution process—extending to parameters not explicitly considered within the simulation environment design. This extensibility remarkably broadens the applicability of our model to explore various other research domains. Besides, our model offers high flexibility by adjusting simulation parameters to simulate a variety of real-world events in the labor market. As shown in Supplementary Section 7, we explored the impact of the emergence of generative large language models like ChatGPT by altering the values of interconnected jobs. In the future, researchers can investigate the influence of different events on job evolution by configuring other simulation parameters. This enhances our understanding of the inherent mechanisms in the labor market's response to external shocks and provides insights and guidance for organizations and labor market regulators when dealing with unforeseen events.

Nonetheless, our model presents certain limitations. Initially, an explicit alignment between our knowledge network and the real world remains challenging. This discrepancy arises due to the vast diversity of knowledge present in the real world and the intricacy of identifying connections among them. Consequently, it becomes unfeasible to map real-world knowledge directly to specific nodes within our network. Hence, the nodes, jobs, and agents in our simulation may not directly correspond to tangible entities in the real world. However, it may be argued that understanding the average effect, disregarding individual discrepancies, could still provide valuable insights. Moreover, striving for an optimal solution for each agent at every time step entails a considerably expansive search space that scales exponentially with the size of the simulation. This impedes our ability to conduct larger-scale simulation experiments. A potential resolution for this limitation involves adopting decision-making methodologies for agents that don't rely on exhaustive search processes. For instance, employing reinforcement learning could offer a viable solution. Through this approach, agents can learn, rather than search, for optimal actions during the simulation, potentially mitigating the challenges posed by extensive search spaces. Finally, in the real-world validation of our study, we selected one of the largest online recruitment platforms in China. Due to differences in national contexts and economic environments, job development and evolution speeds may vary across countries. Understanding these country-specific differences is a direction for our future research, which could provide empirical evidence to support the theoretical basis for differences in job evolution rates between countries.

Conclusion

This study presents a novel computational model to investigate the evolutionary dynamics of job reinvention, revealing the intricate ways in which enterprises adapt and optimize their knowledge resources. By integrating organizational knowledge creation behaviors within a dynamic simulation framework, our research offers a comprehensive perspective on how jobs evolve in response to labor market conditions and organizational strategies.

Building on organizational and knowledge theories, we propose four job evolution mechanisms: knowledge search, knowledge permutation, knowledge reuse, and job transfer. To validate these mechanisms, we conduct a large-scale job posting data analysis, bridging theoretical understanding with empirical evidence and demonstrating their real-world applicability. Our findings reveal that organizations initially depend on external knowledge acquisition but gradually shift toward internal knowledge optimization, marking a key transition in job evolution dynamics. Additionally, we identify non-linear relationships between job evolution intensity and labor market characteristics, offering critical insights into organizational adaptability.

The results have broad implications for researchers, policymakers, and business leaders. For organizations, understanding these mechanisms can inform workforce planning, reskilling initiatives, and innovation strategies. For policymakers, insights into labor market dynamics can guide education and knowledge-sharing policies to foster workforce adaptability in an evolving job landscape. Future research can refine this model by integrating additional external mechanisms and industry-specific constraints while further validating it with global labor market data. This will provide deeper insights into the ongoing evolution of work in the age of AI and digital transformation.

Data availability

The data used and generated in this article have been uploaded to the following link: https://github.com/ZhaoqiZachYang/knowledge-reinvent-jobs. The codes for simulation and real data analysis are also available at the same link.

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References

Bennett VM, Feldman ER (2017) Make room! Make room! A note on sequential spinoffs and acquisitions. Strategy Sci 2:100–110
Benson A, Rissing BA (2020) Strength from within: internal mobility and the retention of high performers. Organ Sci 31:1475–1496
Berchicci L, Dutt N, Mitchell W (2019) Knowledge sources and operational problems: less now, more later. Organ Sci 30:1030–1053
Carnabuci G, Bruggeman J (2009) Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. Soc Forces 88:607–641
Cassiman B, Veugelers R (2006) In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. Manag Sci 52:68–82
Chien C-F, Chen L-F (2007) Using rough set theory to recruit and retain high-potential talents for semiconductor manufacturing. IEEE Trans Semicond Manuf 20:528–541
Chiu C-M, Hsu M-H, Wang ET (2006) Understanding knowledge sharing in virtual communities: an integration of social capital and social cognitive theories. Decis Support Syst 42:1872–1888
Cohen LE, Mahabadi S (2022) In the midst of hiring: pathways of anticipated and accidental job evolution during hiring. Organ Sci 33:1938–1963
Davidsson P, Steffens P, Fitzsimmons J (2009) Growing profitable or growing from profits: putting the horse in front of the cart? J Bus Venturing 24:388–406
Davies A, Brady T (2000) Organisational capabilities and learning in complex product systems: towards repeatable solutions. Res Policy 29:931–953
Denis J-L, Lehoux P, Champagne F (2004) A knowledge utilization perspective on fine-tuning dissemination and contextualizing knowledge. In: Using knowledge and evidence in health care: multidisciplinary perspectives. University of Toronto Press, Toronto
Dencker JC, Gruber M, Shah SK (2009) Pre-entry knowledge, learning, and the survival of new firms. Organ Sci 20:516–537
Easterby-Smith M, Lyles MA, Tsang EW (2008) Inter-organizational knowledge transfer: current themes and future prospects. J Manag Stud 45:677–690
Erika L, Arribill O, Na O (2022) Hybrid working takes hold. Nature 603:537
ESCO (2024) Classification of European skills, competences, and occupations. https://esco.ec.europa.eu/en. Accessed 3 Oct 2024
Gaimon C, Ramachandran K (2021) The knowledge value chain: an operational perspective. Prod Oper Manag 30:715–724
Ghezzi A, Cavallo A (2020) Agile business model innovation in digital entrepreneurship: lean startup approaches. J Bus Res 110:519–537
Groysberg B, Lee L-E (2009) Hiring stars and their colleagues: exploration and exploitation in professional service firms. Organ Sci 20:740–758
Hasan S, Ferguson J-P, Koning R (2015) The lives and deaths of jobs: technical interdependence and survival in a job structure. Organ Sci 26:1665–1681
Hang Y, Zhang Y (2024) The inheritance imperative: a game-theoretic analysis of reverse tacit knowledge transfer. J Knowl Econ 15:18884–18929
Hernandez E, Menon A (2018) Acquisitions, node collapse, and network revolution. Manag Sci 64:1652–1671
Hsu DH, Lim K (2014) Knowledge brokering and organizational innovation: founder imprinting effects. Organ Sci 25:1134–1153
Jesuthasan R, Boudreau J (2018) Reinventing jobs: a 4-step approach for applying automation to work. Harvard Business Press, Boston
Kabir MN (2019) Knowledge-based social entrepreneurship: understanding knowledge economy, innovation, and the future of social entrepreneurship. Springer, New York
Kaur V (2022) Managerial attention and knowledge-based dynamic capabilities: a meta-theoretical approach to competitive advantage. J Gen Manag 03063070221126275
Kneeland MK, Schilling MA, Aharonson BS (2020) Exploring uncharted territory: knowledge search processes in the origination of outlier innovation. Organ Sci 31:535–557
Kotlarsky J, Scarbrough H, Oshri I (2014) Coordinating expertise across knowledge boundaries in offshore-outsourcing projects. MIS Q 38:607–A5
Kyoon Yoo D, Vonderembse MA, Ragu-Nathan T (2011) Knowledge quality: antecedents and consequence in project teams. J Knowl Manag 15:329–343
Långstedt J, Spohr J, Hellström M (2023) Are our values becoming more fit for artificial intelligence society? A longitudinal study of occupational values and occupational susceptibility to technological substitution. Technol Soc 72:102205
Lee CK (2005) Transferability of skills over the IT career path. In: Proceedings of the 2005 ACM SIGMIS CPR conference on computer personnel research, Atlanta. Association for Computing Machinery, New York, p 85–93
Levina N, Vaast E (2005) The emergence of boundary spanning competence in practice: implications for implementation and use of information systems. MIS Q 29:335–363
Li AN, Sherf EN, Tangirala S (2023) Team adaptation to discontinuous task change: equity and equality as facilitators of individual and collective task capabilities redevelopment. Organ Sci 34:1287–1314
Lin C-P (2020) Exploring career commitment and turnover intention of high-tech personnel: a socio-cognitive perspective. Int J Hum Resour Manag 31:760–784
Malone D (2002) Knowledge management: a model for organizational learning. Int J Account Inf Syst 3:111–123
Miles I et al. (1995) Knowledge-intensive business services. In: Users, carriers and sources of innovation. European Commission, Luxembourg
Nair A, Boulton WR (2008) Innovation-oriented operations strategy typology and stage-based model. Int J Oper Prod Manag 28:748–771
Nature (2017) The Future of Work. Nature 550:315
Ng MA (2021) Has the COVID-19 pandemic accelerated the future of work or changed its course? Implications for research and practice. Int J Environ Res Public Health 18:10199
Nujen BB, Halse LL, Damm R, Gammelsæter H (2018) Managing reversed (global) outsourcing—the role of knowledge, technology and time. J Manuf Technol Manag 29:676–698
O*NET (2024) Nation's primary source of occupational information. https://www.onetonline.org/. Accessed 3 Oct 2024
Priyono A, Hidayat A (2022) Dynamic capabilities for open innovation: a typology of pathways toward aligning resources, strategies and capabilities. J Open Innov Technol Mark Complex 8:206
Rafner J, Beaty RE, Kaufman JC, Lubart T, Sherson J (2023) Creativity in the age of generative AI. Nat Hum Behav 7:1836–1838
Randhawa K, Wilden R, Gudergan S (2021) How to innovate toward an ambidextrous business model? The role of dynamic capabilities and market orientation. J Bus Res 130:618–634
Santilli S, Nota L, Hartung PJ (2019) Efficacy of a group career construction intervention with early adolescent youth. J Vocat Behav 111:49–58
Schilling MA Phelps CC (2005) Interfirm collaboration networks: the impact of small world connectivity on firm innovation. Acad Manag Proc 2005:1–6
Sunley P, Martin R, Gardiner B, Pike A (2020) In search of the skilled city: skills and the occupational evolution of British cities. Urban Stud 57:109–133
Tortoriello M, McEvily B, Krackhardt D (2015) Being a catalyst of innovation: the role of knowledge diversity and network closure. Organ Sci 26:423–438
Waheed M, Kaur K (2016) Knowledge quality: a review and a revised conceptual model. Inf Dev 32:271–284
Wallace ML, Larivière V, Gingras Y (2012) A small world of citations? The influence of collaboration networks on citation practices. PLoS ONE 7:e33339
Wang C, Rodan S, Fruin M, Xu X (2014) Knowledge networks, collaboration networks, and exploratory innovation. Acad Manag J 57:484–514
Watts DJ, Strogatz SH (1998) Collective dynamics of 'small-world' networks. Nature 393:440–442
Wei Q, Gu X, Yuan Y (2020) On the structural evolution of the knowledge network and behaviors of the knowledge subjects. J Supercomput 76:3477–3493
Yayavaram S, Ahuja G (2008) Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. Adm Sci Q 53:333–362
Zhou KZ, Li CB (2012) How knowledge affects radical innovation: knowledge base, market knowledge acquisition, and internal knowledge sharing. Strat Manag J 33:1090–1102

Author contributions

YHC: conceptualization, methodology, investigation, formal analysis, data curation, validation, software, resources, writing—original draft, writing—review and editing, supervision. ZQY: conceptualization, methodology, investigation, formal analysis, visualization, validation, software, writing—original draft, writing—review and editing. YC: conceptualization, methodology, validation, software, resources, writing—original draft, writing—review and editing, supervision. YG: conceptualization, methodology, resources, writing—review and editing, supervision, funding acquisition. HSZ: conceptualization, methodology, investigation, formal analysis, resources, writing—original draft, writing—review and editing, supervision, project administration, funding acquisition.

Competing interests

The authors declare no competing interests.

Ethical approval
Ethical approval was not required as the study did not involve human participants.

Informed consent
Informed consent was not required as the study did not involve human participants.

Additional information
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