CARMA 2026

8th Int. Conf. on Advanced Research Methods and Analytics
1-3 July 2026, Valencia, Spain
DOI: https://doi.org/10.4995/CARMA2026.2026.21949

How AI Reshapes Task Demand Structures: Evidence from Korean IT Job (2018 – 2022)

Jihwan Sim[1]

[1]Department of Big Data Management, Dongyang Mirae University, Seoul, South Korea.

How to cite: Sim, J. (2026) How AI Reshapes Task Demand Structures: Evidence from Korean IT Job (2018 – 2022). In: 8th International Conference on Advanced Research Methods and Analytics (CARMA 2026). Valencia, 1-3 July 2026. https://doi.org/10.4995/CARMA2026.2026.21949

Abstract

The rapid diffusion of artificial intelligence (AI) has reshaped skill demand in IT labor markets, yet empirical evidence from non-Western economies remains limited. This study analyzes how demanded skill structures evolved in the South Korean IT labor market between 2018 and 2022, using co-occurrence network analysis and association rule mining on 902,638 online job postings. Demanded skills are grouped into 59 task-level categories to capture skill-bundle architecture in line with the task-based labor market tradition. The results reveal a structural centrality shift from soft-skill-dominated configurations toward AI- and data-engineering-centered ones. Association rule mining further uncovers persistent soft–hard skill interdependencies throughout this transformation. These findings extend AI-driven labor market evidence to a non-English-speaking context and inform workforce development policy and educational planning.

Keywords: *labor market intelligence; task co-occurrence network; AI skill demand; soft–hard skill interdependency; job posting analysis*

1. Introduction

The task-based approach (Autor et al., 2003) reoriented labor market analysis from occupations to tasks, recognizing that technology affects specific task components rather than entire jobs. Building on this foundation, the skill-spaces literature has shown that the relational structure of skills—how skills cluster, complement, and depend on one another—governs both wage formation and labor mobility: workers benefit from complementary co-workers (Neffke, 2019), skill prices are determined by complementarity rather than scarcity (Stephany & Teutloff, 2024), and broader skill portfolios exhibit nested human-capital architectures (Hosseinioun et al., 2025). The emergence of AI has accelerated these dynamics, with Alekseeva et al. (2021) documenting a tenfold increase in AI-related job postings in the U.S. between 2010 and 2019. Online job postings have become a key data source for studying these shifts (Colombo et al.,

Article in Press

This work is licensed under a Creative Commons License CC BY-NC-SA 4.0
Editorial Universitat Politècnica de València

2019), and network-based approaches have demonstrated their ability to reveal structural properties of labor markets beyond frequency-based analyses (Alabdulkareem et al., 2018; Neffke et al., 2024).

However, the existing literature exhibits two notable gaps. First, computational job market analyses overwhelmingly focus on English-speaking countries (Senger et al., 2024), leaving non-Western economies underexplored. South Korea, with its IT workforce expanding from 532,000 (2017) to over 680,000 (2022) (Ministry of Science and ICT, 2023), is a compelling yet understudied case. Second, structural interdependencies between soft skills and hard skills have received limited quantitative attention, despite qualitative evidence of their importance in IT occupations (Stevens & Norman, 2016; Ternikov, 2022).

This study addresses these gaps by analyzing Korean IT job postings with task-level skill labels from a 59-category taxonomy. We pursue three objectives: (RO1) track the evolution of demanded skill–task structures using co-occurrence network analysis, (RO2) identify shifts in central bridging skill clusters through betweenness centrality, and (RO3) quantify soft–hard skill interdependencies through association rule mining.

2. Data and Methodology

2.1. Data Description

The dataset comprises 902,638 IT job postings collected from Saramin and JobKorea—South Korea's two largest online recruitment platforms—covering January 2017 to December 2022. These postings span 25 occupational categories classified under the Korean Employment Classification of Occupations (KECO), encompassing IT research and development, engineering, and installation/maintenance roles. Online job postings primarily capture employer-side skill demand rather than the actual performance of tasks (Colombo et al., 2019); accordingly, our analysis characterizes demanded skill bundles, which we organize into task-level categories as a proxy for the underlying task structure of IT jobs. Table 1 summarizes the annual distribution.

Table 1. Distribution of IT job postings by year.

Year	2018	2019	2020	2021	2022	Total
Count	88,427	96,957	100,888	235,243	381,123	902,638

The dataset exhibits substantial growth, with annual postings increasing more than fourfold from 2018 to 2022, reflecting the expanding demand for IT professionals. Each posting is associated with one or more task-level skill labels from a standardized taxonomy of 59 categories, organized in a hierarchical three-digit coding system. The taxonomy was constructed

Article in Press

through embedding-based hierarchical clustering of skill terms extracted from postings, followed by expert validation by two labor economics specialists. Major categories include web development, application development, data engineering, AI planning, leadership, and various infrastructure and security operations.

Soft skills are assigned to major category 9 in the taxonomy and include leadership (project management, IT planning, supervision), personality traits (positive attitude, diligence, communication), language proficiency (bilingual, TOEIC, JLPT), and collaboration (teamwork, communication skills). All remaining categories constitute hard (technical) skills.

2.2. Task Co-occurrence Network Construction

We constructed annual skill–task co-occurrence networks for each year from 2018 to 2022. The year 2017 was excluded due to limited sample size and distributional skewness that would compromise centrality measurements. In each network:

- Nodes represent the 59 task-level skill categories.
- Edges connect two categories that co-occur within the same job posting, with edge weights defined as the co-occurrence frequency.
- Betweenness centrality is computed for each node to identify categories that serve as critical bridges in the demand structure:

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of those paths passing through v. High betweenness centrality indicates that a category functions as a key connector across diverse skill domains.

2.3. Association Rule Mining

To quantify soft–hard skill interdependencies beyond what network topology reveals, we applied the Apriori algorithm for association rule mining. Three standard metrics are computed:

- Support: $P(A \cap B)$ – the proportion of postings containing both A and B.
- Confidence: $P(B \mid A)$ – the conditional probability of B given A.
- Lift: $P(B \mid A) \,/\, P(B)$ – the degree to which the presence of A increases the probability of B. A lift greater than 1.0 indicates a positive association beyond chance.

We set thresholds of support ≥ 0.003 and lift > 1.0 to filter meaningful associations. The analysis focuses on rules where soft skills (taxonomy code starting with 9) appear as antecedents, revealing which technical competencies are most strongly demanded in conjunction with interpersonal and managerial capabilities.

Article in Press

3. Results

3.1. Task Demand Evolution

Web development consistently accounted for the largest share of task mentions, with leadership and intermediate-level development maintaining steady demand. From 2021, web development and DB development showed sharp proportional increases. Soft-skill-related tasks persisted alongside dominant technical tasks throughout, consistent with prior findings (Stevens & Norman, 2016).

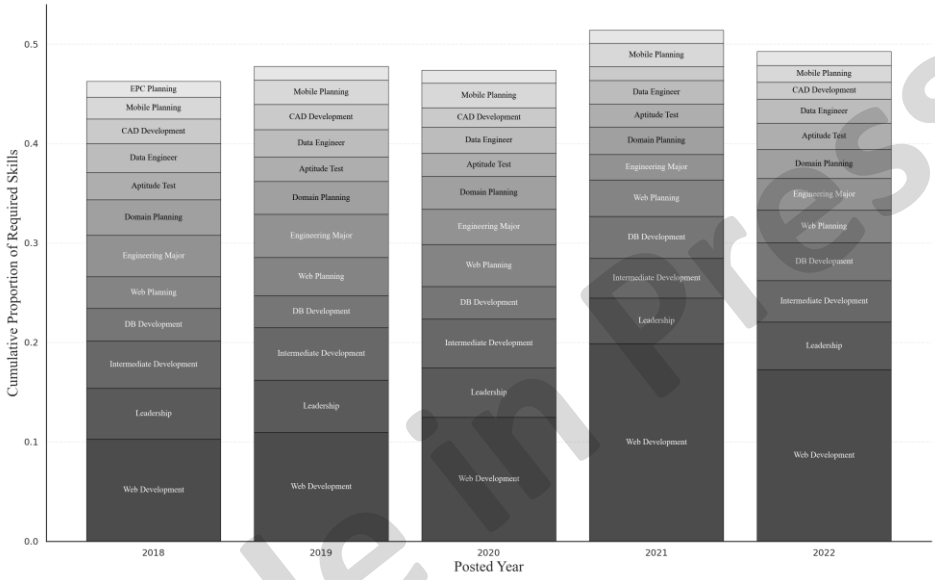


Figure 1. Year-by-year proportion changes of the top 5 most frequent tasks (2018–2022).

3.2. Centrality Shifts in Task Co-occurrence Networks (2018–2022)

3.2.1. Phase 1: Soft-Skill Dominance (2018–2019)

In 2018, the highest betweenness centrality scores were observed for intermediate development, domain planning, engineering major, language proficiency, leadership, QA planning, and architecture planning. The 2019 network exhibited a similar structure, with domain planning, technical support, engineering major, leadership, language proficiency, QA planning, and architecture planning maintaining high centrality. The prominence of soft skills—particularly leadership and language proficiency—as central bridging categories indicates that managerial and communication competencies served as key connectors across diverse technical domains during this period.

Article in Press

3.2.2. Phase 2: Transition (2020)

The 2020 network introduced two new high-centrality categories: fintech planning and technical sales. While the emergence of fintech planning may reflect growing demand for financial technology services, the broader structural pattern remained largely consistent with the preceding phase.

3.2.3. Phase 3: AI-Driven Transformation (2021–2022)

A pronounced structural shift occurred in 2021, when data engineering, business support, electronics development, and web planning emerged as high-centrality categories. By 2022, AI planning ascended to become one of the most central nodes, alongside architecture planning. This transition mirrors findings from the U.S. labor market, where Alekseeva et al. (2021) documented the highest AI skill demand in IT occupations.

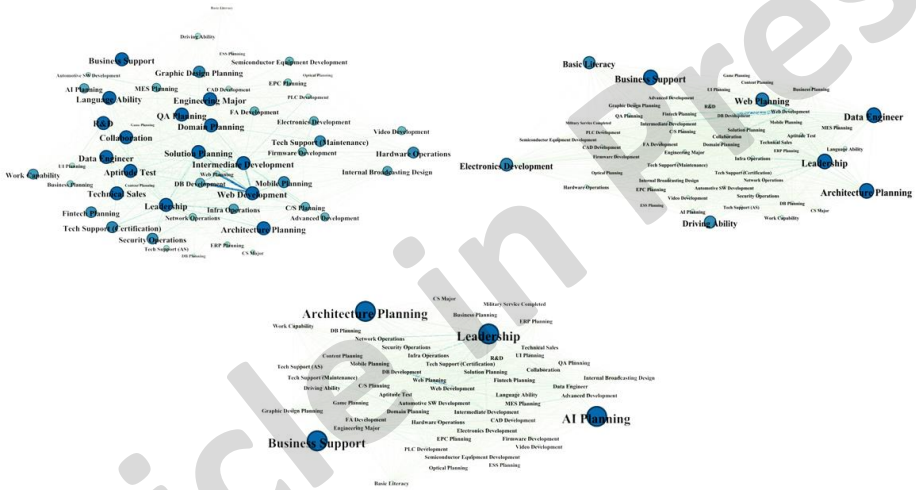


Figure 2. Task co-occurrence networks for 2019 (top-left), 2021 (top-right), and 2022 (bottom-center). Node size is proportional to betweenness centrality; edge thickness is proportional to connection strength.

3.3. Connection Strength Analysis

To characterize the neighborhoods of newly central categories, we examined connection strength (co-occurrence frequency) for data engineering in 2021 and AI planning in 2022 (Tables 2 and 3).

Article in Press

Table 2. Top 5 most strongly co-occurring categories with Data Engineering (2021).

Rank	Connected Category	Connection Strength
1	Leadership	1,801
2	DB Development	1,785
3	Domain Planning	1,755
4	Intermediate Development	1,723
5	Web Development	1,554

Table 3. Top 5 most strongly co-occurring categories with AI Planning (2022).

Rank	Connected Category	Connection Strength
1	Data Engineering	1,892
2	Intermediate Development	1,604
3	Domain Planning	1,174
4	Video/Image Development	792
5	Leadership	481

Data engineering and AI planning exhibit strong mutual co-occurrence—AI planning ranked 6th for data engineering in 2021, while data engineering ranked 1st for AI planning in 2022—indicating a tightly coupled cluster. Soft skills (leadership, personality traits) also appear prominently alongside these technical categories.

3.4. Soft–Hard Skill Interdependencies

The association rule analysis quantifies the strength of soft–hard skill interdependencies across the full dataset. Table 4 presents selected rules with the highest lift values.

Table 4. Selected association rules: Soft skills → Hard skills (support ≥ 0.003, lift > 1.0).

Antecedent	Consequent	Support	Confidence	Lift
Leadership	Infrastructure Operation	0.0045	0.355	8.04
Leadership	Network Operation	0.0045	0.262	6.67
Leadership	Architecture Planning	0.0104	0.099	3.14
Personality	Security Operation	0.0041	0.068	1.66
Personality	Data Engineering	0.0047	0.078	1.40
Collaboration	R&D	0.0068	0.176	1.67
Collaboration	Data Engineering	0.0031	0.082	1.47

Leadership shows the strongest associations with infrastructure-level categories (lift > 6.0), while personality traits and collaboration are consistently associated with emerging technical categories including data engineering.

Article in Press

Table 5. Year-specific association rules for emerging central categories.

Year	Antecedent	Consequent	Support	Confidence	Lift
2021	Data Engineering	AI Planning	0.0042	0.082	5.37
2021	Data Engineering	DB Planning	0.0030	0.060	2.87
2022	AI Planning	Data Engineering	0.0039	0.245	4.79
2022	Architecture Planning	Leadership	0.0086	0.320	3.13
2022	Architecture Planning	Infrastructure Operation	0.0036	0.133	3.05

The bidirectional association between data engineering and AI planning (lift: 5.37 in 2021; 4.79 in 2022) provides statistical evidence for the formation of a cohesive AI–data engineering cluster.

4. Discussion and Conclusion

The centrality shift from soft-skill-centered (2018–2019) to AI- and data-engineering-centered (2021–2022) task configurations is consistent with global trends (Alekseeva et al., 2021; Acemoglu & Restrepo, 2019) and extends them to a non-Western context. The tightly coupled AI–data engineering cluster signals that Korea's IT industry is building AI infrastructure that demands combined competencies, aligning with skill-complementarity logic (Neffke, 2019; Stephany & Teutloff, 2024). Persistent soft–hard skill interdependencies further indicate that growing technical complexity increases rather than diminishes the demand for interpersonal skills (Stevens & Norman, 2016; Ternikov, 2022), resonating with the nested human-capital architecture documented at the global scale (Hosseinioun et al., 2025).

These findings call for integrated AI–data engineering curricula, workforce-development programs that combine technical upskilling with soft-skill training, and HR strategies that prioritize "T-shaped professionals" with both technical and interpersonal capabilities.

Several limitations should be noted. First, online job postings reflect employer-side demand and may suffer from selection bias; the volume increase from 88,427 (2018) to 381,123 (2022) implies that earlier-year networks rest on smaller samples and should be interpreted as trend indicators rather than precise structural snapshots. Second, the analysis is restricted to the IT sector and two platforms, and may not capture short-term project-based or informal hiring. Third, the period ending in 2022 does not reflect the generative AI wave. Future work could apply causal inference, cross-country comparisons, and statistical filtering toolboxes for non-random link extraction (Aufiero et al., 2024) to further contextualize these findings.

Article in Press

Acknowledgements.

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2025S1A5A8004633).

References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Alabdulkareem, A., Frank, M. R., Sun, L., AlShebli, B., Hidalgo, C., & Rahwan, I. (2018). Unpacking the polarization of workplace skills. Science Advances, 4(7), eaao6030. https://doi.org/10.1126/sciadv.aao6030

Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. Labour Economics, 71, 102002. https://doi.org/10.1016/j.labeco.2021.102002

Aufiero, S., De Marzo, G., Sbardella, A., & Zaccaria, A. (2024). Mapping job fitness and skill coherence into wages: An economic complexity analysis. Scientific Reports, 14, 11752. https://doi.org/10.1038/s41598-024-61448-x

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics, 118(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Colombo, E., Mercorio, F., & Mezzanzanica, M. (2019). AI meets labor market: Exploring the link between automation and skills. Information Economics and Policy, 47, 27–37. https://doi.org/10.1016/j.infoecopol.2019.05.003

Hosseinioun, M., Neffke, F., Zhang, L., & Youn, H. (2025). Skill dependencies uncover nested human capital. Nature Human Behaviour, 9(4), 673–687. https://doi.org/10.1038/s41562-024-02093-2

Ministry of Science and ICT. (2023). 2022 Survey on the IT Industry Workforce. Government of the Republic of Korea.

Neffke, F. M. H. (2019). The value of complementary co-workers. Science Advances, 5(12), eaax3370. https://doi.org/10.1126/sciadv.aax3370

Neffke, F., Nedelkoska, L., & Wiederhold, S. (2024). Skill mismatch and the costs of job displacement. Research Policy, 53(2), 104933. https://doi.org/10.1016/j.respol.2023.104933

Senger, E., Zhang, M., van der Goot, R., & Plank, B. (2024). Deep learning-based computational job market analysis: A survey on skill extraction and classification from job postings. In Proceedings of the First Workshop on Natural Language Processing for Human Resources (NLP4HR 2024) (pp. 1–15). Association for Computational Linguistics. https://doi.org/10.18653/v1/2024.nlp4hr-1.1

Stephany, F., & Teutloff, O. (2024). What is the price of a skill? The value of complementarity. Research Policy, 53(1), 104898. https://doi.org/10.1016/j.respol.2023.104898

Article in Press

Stevens, M., & Norman, R. (2016). Industry expectations of soft skills in IT graduates: A regional survey. In Proceedings of the Australasian Computer Science Week Multiconference (Article 13, pp. 1–9). ACM. https://doi.org/10.1145/2843043.2843068

Ternikov, A. (2022). Soft and hard skills identification: Insights from IT job advertisements in the CIS region. PeerJ Computer Science, 8, e946. https://doi.org/10.7717/peerj-cs.946

Article in Press