Improving Competitiveness: A Freelancer-Centric Approach for Recommending Reskilling Strategies

Haoxin Liu
School of Management, University of Science and Technology of China, Hefei, Anhui 230026, China
hxliu1215@ustc.edu.cn

Shuo Yu
Area of Information Systems and Quantitative Sciences, Rawls College of Business, Texas Tech University, Lubbock, TX 79409
Shuo.Yu@ttu.edu

Stephen He
Department of Marketing, Alvarez College of Business, University of Texas at San Antonio, San Antonio, TX 78249
Stephen.He@utsa.edu

Wen Wen
Department of Information, Risk & Operations Management, McCombs School of Business, University of Texas at Austin, Austin, TX 78712
Wen.Wen@mccombs.utexas.edu

Yidong Chai
Department of Information Systems, City University of Hong Kong, Hong Kong 999077, China
School of Management, Hefei University of Technology, Hefei, Anhui 230009, China
Business Artificial Intelligence Laboratory, City University of Hong Kong (Dongguan), Dongguan, Guangdong 523808, China
yidongchai@gmail.com

ONLINE APPENDICES

Online Appendix A: Literature Review Tables

Year	Author	Reskilling Basis	Methodological Approach
2025	Sun et al.	Long-term return	Deep reinforcement learning
2024	Decorte et al.	Job post requirement	Sentence-BERT
2023	Ong & Lim	Job title	BERT/FastText embedding
2022	Gandhi et al.	Job post requirement	Word2vec/BERT embedding
2021	Kokkodis & Ipeirotis	Long-term return	Word2vec embedding, reinforcement learning
2021	Sun et al.	Long-term return	Deep reinforcement learning
2020	Ghosh et al.	Job title	Monotonic nonlinear state-space
2019	Wu et al.	Market demand and trend	Tensor factorization
2018	Dave et al.	Job title	BPR embedding
2017	Patel et al.	Similar peers, job post requirement	Simple heuristics
2017	Maurya & Telang	Market demand, similar peers	Bayesian multi-view clustering

Table A1. Selected Recent Literature on Skill Recommender Systems

Year	Author	Skill Representation Method	Freelancer and Task Skills Matching Method	Explanation for Recommendation
2025	Rosenberger et al.	CareerBERT	Cosine similarity	N/A
2024	Han et al.	N/A	N/A	N/A
2024	Guan et al.	TextCNN with Transformer	N/A	N/A
2023	Wang et al.	Manually grouped into 6 types	N/A	N/A
2023	Kokkodis & Ipeirotis	Word2vec embedding	Inner product	N/A
2021	Yuen et al.	N/A	N/A	N/A
2020	Bian et al.	N/A (skills are part of resume text, no explicit representation)	N/A	Highlighting relevant keywords
2020	Abhinav et al.	One-hot encoding with skill co-occurrence matrix	Modified counting of common skills	Ranking important features
2020	Qin et al.	N/A (skills are part of resume text, no explicit representation)	N/A	Highlighting relevant keywords
2020	Dai et al.	N/A	N/A	N/A
2019	Hossain & Arefin	One-hot encoding	Counting common skills	N/A
2018	Zhu et al.	N/A (skills are part of resume text, no explicit representation)	N/A	N/A
2018	Dave et al.	BPR embedding (for both jobs and skills)	Inner product (matching a skill to a job title)	N/A
2017	Patel et al.	One-hot encoding	K-nearest neighbors	N/A

Table A2. Selected Recent Literature on Task Recommender Systems

Online Appendix B: Details of the Popularity and Proficiency Coefficients

A proper measure of the popularity of skill c_j should capture how frequently it has been requested in past task posts, while giving less weight to older tasks. We therefore define the time-discounted popularity count of skill c_j, denoted π_{c_j}, as follows:

$$\pi_{c_j} = \sum_{t_i \in \theta_{c_j}} \exp(-\beta(year_0 - year_{t_i})),$$

where θ_{c_j} denotes the set of past tasks requiring skill c_j, $year_0$ denotes the current year, $year_{t_i}$ is the completion year of task t_i, and β is a constant controlling the time decay rate. Next, we define the logarithmic time-discounted popularity count of skill c_j, denoted λ_{c_j}, as:

$$\lambda_{c_j} = \log_2\left(\pi_{c_j} + 1\right),$$

which ensures that λ_{c_j} does not grow too quickly and that $\lambda_{c_j} = 0$ when $\pi_{c_j} = 0$. Finally, we min-max normalize λ_{c_j} across all skills to obtain the scaled popularity-based opportunity cost coefficient ψ_{c_j}:

$$\psi_{c_j} = 1 - \frac{\lambda_{c_j} - \min\left(\lambda_{c_j}\right)}{\max\left(\lambda_{c_j}\right) - \min\left(\lambda_{c_j}\right)},$$

such that ψ_{c_j} is bounded between 0 and 1. Note that a larger λ_{c_j} (greater popularity) yields a smaller ψ_{c_j}.

A proper measure of the proficiency of freelancer r_m should capture their mastery of high-quality and complex skills in the completion of tasks. Since we lack a direct measure of a skill's quality or complexity, we use the average hourly wage of tasks requiring that skill as a proxy. This is because tasks with higher hourly wages are more likely to demand higher-quality and more complex skills.

For instance, tasks requiring the skill "Python" have an average hourly wage of $117, whereas tasks requiring the skill "Word" have an average hourly wage of $88. Accordingly, we set the quality level of "Python" to 117 and that of "Word" to 88. A freelancer's overall proficiency is then proxied by the sum of the quality levels of all their skills.

Formally, we denote $c_{r_m i}$ as the i-th skill possessed by freelancer r_m, and denote $G(c_{r_m,i})$ as the average hourly wage of tasks that requiring skill $c_{r_m i}$ (i.e., the quality level of the skill). We define the proficiency of freelancer r_m, denoted I_{r_m}, as follows:

$$I_{r_m} = \sum_{i=1}^{B} G(c_{r_m,i})$$

where B is the total number of skills possessed by freelancer r_m.

Next, we min-max normalize I_{r_m} across all freelancers to yield the proficiency-based scaled extra cost coefficient ϕ_{r_m}:

$$\phi_{r_m} = 1 - \frac{I_{r_m} - \min(I_{r_m})}{\max(I_{r_m}) - \min(I_{r_m})},$$

such that ϕ_{r_m} lies between 0 and 1. Note that larger I_{r_m} (greater proficiency) yields a smaller ϕ_{r_m}.

Online Appendix C: Proof that the Learning Cost Is Irrelevant to the Learning Order

Assuming $\delta = [c_1, \dots, c_h, \dots, c_H]$ and $\delta' = [c'_1, \dots, c'_h, \dots, c'_H]$ are two different permutations of the same skill set σ, where $H = |\sigma|$ is the cardinality of σ. The learning costs under these two different learning orders are:

$$\operatorname{cost}(\sigma; \delta; r_m) = \sum_{h=1}^{H} 1 - (\boldsymbol{e}_{c_h})^{\mathrm{T}}(\boldsymbol{e}^{s}_{r_m} + \sum_{i=1}^{h-1} \boldsymbol{e}_{c_i}),$$

$$\operatorname{cost}(\sigma; \delta'; r_m) = \sum_{h=1}^{H} 1 - (\boldsymbol{e}_{c'_h})^{\mathrm{T}}(\boldsymbol{e}^{s}_{r_m} + \sum_{i=1}^{h-1} \boldsymbol{e}_{c'_i}).$$

The difference between the two is:

$$\begin{aligned}
\operatorname{cost}(\sigma; \delta; r_m) - \operatorname{cost}(\sigma; \delta'; r_m) &= \sum_{h=1}^{H} (1 - \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}} (\boldsymbol{e}^{s}_{r_m} + \sum_{i=1}^{h-1} \boldsymbol{e}_{c_i})) - \sum_{h=1}^{H} (1 - \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} (\boldsymbol{e}^{s}_{r_m} + \sum_{i=1}^{h-1} \boldsymbol{e}_{c'_i})) \\
&= -\sum_{h=1}^{H} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}} \boldsymbol{e}^{s}_{r_m} - \sum_{h=1}^{H} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}} \left(\sum_{i=1}^{h-1} \boldsymbol{e}_{c_i}\right) + \sum_{h=1}^{H} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} \boldsymbol{e}^{s}_{r_m} + \sum_{h=1}^{H} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} \left(\sum_{i=1}^{h-1} \boldsymbol{e}_{c'_i}\right) \\
&= \boldsymbol{e}^{s}_{r_m} \left(\sum_{h=1}^{H} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} - \sum_{h=1}^{H} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}}\right) + \left(\sum_{h=1}^{H} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} \left(\sum_{i=1}^{h-1} \boldsymbol{e}_{c'_i}\right) - \sum_{h=1}^{H} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}} \left(\sum_{i=1}^{h-1} \boldsymbol{e}_{c_i}\right)\right) \\
&= \boldsymbol{e}^{s}_{r_m} \left(\sum_{h=1}^{H} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} - \sum_{h=1}^{H} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}}\right) + \left(\sum_{h=1}^{H} \sum_{i=1}^{h-1} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} \boldsymbol{e}_{c'_i} - \sum_{h=1}^{H} \sum_{i=1}^{h-1} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}} \boldsymbol{e}_{c_i}\right)
\end{aligned}$$

Both $\sum_{h=1}^{H} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}}$ and $\sum_{h=1}^{H} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}}$ refer to the sum of the embeddings of skills in σ, which are identical regardless of the order. Thus, their difference is 0.

Similarly, both $\sum_{h=1}^{H} \sum_{i=1}^{h-1} \left(\boldsymbol{e}_{c'_h}\right)^{\mathrm{T}} \boldsymbol{e}_{c'_i}$ and $\sum_{h=1}^{H} \sum_{i=1}^{h-1} \left(\boldsymbol{e}_{c_h}\right)^{\mathrm{T}} \boldsymbol{e}_{c_i}$ represent the sum of all pairwise inner products of the embeddings of skills in σ. Since the set σ is unchanged, these sums are also identical, and their difference is 0.

Therefore, $\operatorname{cost}(\sigma; \delta; r_m) - \operatorname{cost}(\sigma; \delta'; r_m) = 0$. In other words, the learning cost $\operatorname{cost}(\sigma; \delta; r_m)$ is independent of the order in which the skills are learned, and hence is irrelevant to the learning order.

Online Appendix D (Case Study 1): Examples of Freelancer-Task Matching

We illustrate how our system matches freelancers to suitable tasks using two freelancer profiles and five matched tasks for each (Table D1). For each freelancer, we provide their number of reviews, country of origin, title, and current skillset. For each matched task, we present the task title and required skillset.

Freelancer 1	**# Reviews Received**	730	**Country of Origin**	Venezuela
Title	SEO Master - Real Quality Backlinks			
Freelancer Skillset	SEO, Internet Marketing, Link Building, Marketing, Article Writing, Blog, Search Engine Marketing, Photography, Social Media Marketing			
Task 1	SEO digital marketing for website			
Skillset	SEO, Link Building, Internet Marketing, Marketing, Search Engine Marketing			
Task 2	I need SEO for my website			
Skillset	Internet Marketing, Link Building, Marketing, Search Engine Marketing, SEO			
Task 3	For 2021 SEO Work for WEBSRANKER			
Skillset	SEO, Link Building, Internet Marketing, Marketing, Search Engine Marketing			
Task 4	Wix Web store SEO Link Building, Marketing, Search Engine Marketing			
Skillset	Internet Marketing, Link Building, Marketing, Search Engine Marketing, SEO			
Task 5	SEO for my website			
Skillset	Internet Marketing, Link Building, Marketing, Search Engine Marketing, SEO			

Freelancer 2	**# Reviews Received**	357	**Country of Origin**	Venezuela
Title	Wordpress Expert, 3D LOGO, Website Design			
Freelancer Skillset	Website Design, HTML, PHP, Graphic Design, WordPress, HTML5, MySQL, SEO, Blog Install			
Task 1	Design Conversion and Setup on Wordpress			
Skillset	Anything Goes, Blog, CSS, SEO, Social Networking, Website Design, WordPress, XML			
Task 2	Convert a Template to a Website			
Skillset	Adobe Flash, HTML, PHP, PSD to HTML, Website Design			
Task 3	Create a CSS Stylesheet for Simple Mobile Website			
Skillset	CSS, HTML5, PHP, PSD to HTML, Website Design			
Task 4	Convert PSD to HTML to Building Wordpress Website			
Skillset	PSD to HTML, HTML, WordPress, Website Design, PHP			
Task 5	PSD to Joomla Website (or Wordpress)			
Skillset	CSS, HTML, Joomla, PHP, WordPress			

Table D1. Examples of Tasks Recommended to Freelancers

Freelancer 1 demonstrates expertise in Search Engine Optimization (SEO). Accordingly, the system matched them with tasks emphasizing Internet Marketing and SEO. In contrast, Freelancer 2 exhibits competence in Website Design. The system matched them with tasks such as WordPress setup, template-to-website conversion, and PSD-to-HTML integration. These examples show that our system effectively identifies task opportunities aligned with freelancers' skills, thereby enhancing the relevance and quality of freelancer–task matches.

Online Appendix E (Case Study 2): Examples of Skill Embeddings

A key feature of skill embeddings is that semantically similar skills should be located close to each other in the embedding space. To visually examine this property, we applied Principal Component Analysis (PCA) to reduce the dimensionality of the learned skill embeddings and plotted them based on the two most significant components, which serve as the horizontal and vertical axes in Figure E1. This approach follows established practices in the literature (e.g., Kokkodis 2021). We specifically examined two sets of cases: (1) similar skills with partially shared names, and (2) similar skills with distinct names.

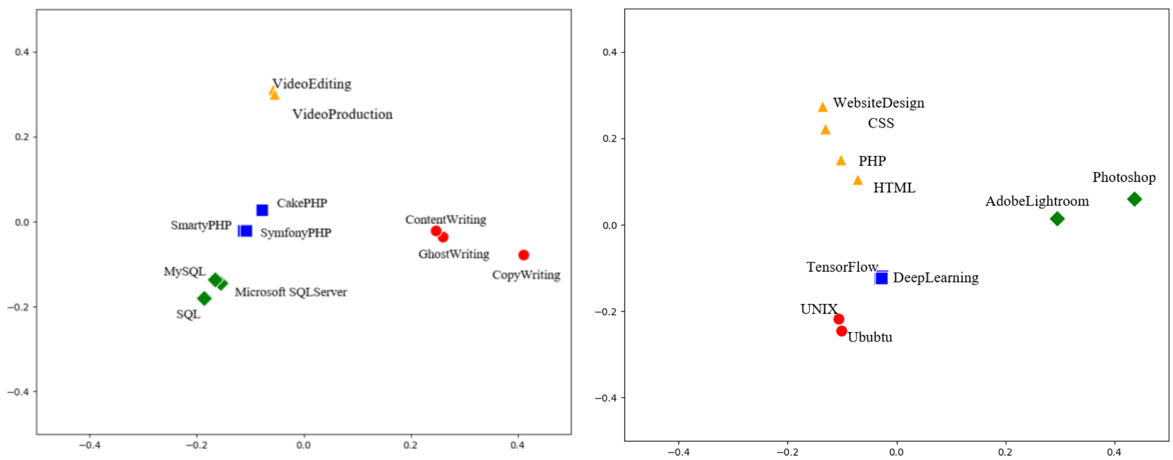

Figure E1. Skill Embeddings Mapped into a Two-Dimensional Space

In the first sub-figure, four clusters emerge that correspond to *video*, *writing*, *PHP*, and *SQL*. In the second sub-figure, semantically related skills without shared names also cluster together. Examples include *web design* (HTML, CSS, PHP, WebsiteDesign), *operating systems* (UNIX, Ubuntu), *algorithms* (DeepLearning, Tensorflow), and *photo editing* (Photoshop, Adobe Lightroom). These clustering patterns provide evidence for the efficacy of our design. Specifically, they demonstrate that the embeddings jointly learned with the recommender through contrastive learning capture meaningful semantic relationships among skills.

Online Appendix F (Case Study 3): Examples of Skill Advice to Freelancers

We illustrate how our skill advisor provides guidance to freelancers who are interested in tasks for which they are not yet competitive. Table F1 presents seven freelancer-task pairs, including the freelancers' existing skillsets, the skills required by the tasks, and the skill advice generated by our advisor.

Freelancer 1 Skillset	WebsiteDesign, WordPress, GraphicDesign, JavaScript, CSS, jQuery/Prototype, PSDtoHTML, BannerDesign, LogoDesign
Task Category	Web Design
Task Skill Req.	CSS, HTML, jQuery / Prototype, PSD to HTML
Skill Advice	*HTML*

Freelancer 2 Skillset	SEO, LinkBuilding, InternetMarketing, Marketing, GoogleAdwords, SearchEngineMarketing, ArticleSubmission, Advertising, WordPress
Task Category	Marketing
Task Skill Req.	InternetMarketing, Marketing, Sales, SEO, WebsiteDesign
Skill Advice	*SocialMediaMarketing*

Freelancer 3 Skillset	WebScraping, C#Programming, .NET, SoftwareArchitecture, PHP, Excel, DataMining, MySQL, HTML
Task Category	Data Processing
Task Skill Req.	DataEntry, Excel, WebScraping, WebSearch
Skill Advice	*Python*

Freelancer 4 Skillset	HTML, WebsiteDesign, PHP, CSS, GraphicDesign, WordPress, Shopify, PSDtoHTML, Photoshop
Task Category	Graphic & Photo
Task Skill Req.	GraphicDesign, LogoDesign, WebsiteDesign, BrochureDesign, CorporateIdentity
Skill Advice	*3DModelling, Illustrator*

Freelancer 5 Skillset	GraphicDesign, ConceptDesign, AfterEffects, Photoshop, Twitter, Animation, VideoEditing, PHP, BannerDesign
Task Category	Animation
Task Skill Req.	VideoServices, AfterEffects, GraphicDesign, VideoProduction, ExplainerVideos
Skill Advice	*VideoServices, PhotoEditing*

Freelancer 6 Skillset	EnglishUSTranslator, DataEntry, FrenchTranslator, ArticleWriting, Translation, CopyTyping, EnglishUKTranslator, Proofreading, VirtualAssistant
Task Category	Translation
Task Skill Req.	Translation, EnglishUSTranslator, EnglishUKTranslator, HTML, Proofreading
Skill Advice	*BusinessWriting, Editing*

Freelancer 7 Skillset	ArticleWriting, ResearchWriting, ReportWriting, AbnormalPsychology, AcademicAdministration, TechnicalWriting, ContentWriting, Research, Copywriting
Task Category	Business
Task Skill Req.	BusinessAnalysis, BusinessIntelligence, BusinessWriting, ReportWriting, ResearchWriting
Skill Advice	*BusinessPlans*

Table F1. Examples of Skill Advice to Freelancers

We observe two key patterns. When a task explicitly requires a skill the freelancer lacks, the advisor naturally recommends that skill (e.g., *HTML* for Freelancer 1). Second, beyond missing requirements, the advisor also recommends complementary skills that enhance competitiveness in the target domain (e.g., *SocialMediaMarketing* for Freelancer 2 in Marketing; *Python* for Freelancer 3 in Data Processing). Together, these patterns demonstrate that the skill advisor generates targeted and contextually relevant recommendations, supporting freelancers' reskilling decisions and long-term career development.

Online Appendix G: Model Generalizability Analysis on a New Dataset

In this section, we demonstrate the generalizability of our proposed FESA by applying the model to a newly collected dataset. This dataset, obtained in April 2024 from a major online labor market, comprises 1,884 freelancers, 41,027 completed tasks, and 1,615 distinct skills. Among the freelancers, 1,834 distinct skillsets are observed, suggesting that nearly every freelancer has a unique combination of skills. In contrast, the 41,027 tasks exhibit 12,865 distinct skill requirements.

To simulate a realistic scenario where a model trained on an earlier dataset must be applied to an evolving online labor market, we directly applied the model trained on the 2022 dataset to the 2024 dataset and assessed its generalizability.

Since the original dataset was collected, many new skills have emerged. Because the model jointly learns skill embeddings during training, embeddings for these newly introduced skills are not available, creating an out-of-vocabulary challenge commonly encountered in natural language processing. Following established approaches (e.g., Garneau et al. 2019; Khodak et al. 2018), we address this issue by substituting the embeddings of unseen skills with the average embeddings of other skills in the freelancer's profile (or in the task post's requirements) that already have embeddings available.

Tables G1, G2, Figure G1, and Table G3 report the results of Evaluation 1: Evaluating Freelancer Competitiveness, Evaluation 2: Alternative Skill Embedding Methods, Evaluation 4: Skill Advisor for Improving Freelancer Competitiveness, and Evaluation 5: Skill Advice Diversity Analysis, respectively. Across all evaluations, our proposed FESA significantly outperformed the benchmark methods ($p < .001$; significance notations are omitted in the tables), consistent with the findings reported in Section 4 of the main manuscript.

Method	K = 10			K = 20			K = 30		
	HR	MRR	NDCG	HR	MRR	NDCG	HR	MRR	NDCG
Apriori	0.2005 ±0.0025	0.0360 ±0.0010	0.0710 ±0.0010	0.2990 ±0.0040	0.0400 ±0.0010	0.0915 ±0.0015	0.3985 ±0.0095	0.0430 ±0.0010	0.1105 ±0.0025
LSA	0.3028 ±0.0022	0.0330 ±0.0007	0.0875 ±0.0005	0.5775 ±0.0027	0.0443 ±0.0004	0.1460 ±0.0007	0.7623 ±0.0026	0.0493 ±0.0004	0.1818 ±0.0004
TextMatch	0.1965 ±0.0045	0.0355 ±0.0005	0.0690 ±0.0010	0.2975 ±0.0005	0.0395 ±0.0005	0.0910 ±0.0003	0.3960 ±0.0050	0.0425 ±0.0005	0.1100 ±0.0010
SkillText Match	0.0990 ±0.0043	0.0300 ±0.0008	0.0457 ±0.0017	0.1960 ±0.0073	0.0363 ±0.0012	0.0697 ±0.0024	0.2980 ±0.0079	0.0403 ±0.0012	0.0917 ±0.0024
TasRec	0.6075 ±0.0065	0.2595 ±0.0075	0.3410 ±0.0070	0.7770 ±0.0020	0.2715 ±0.0065	0.3840 ±0.0050	0.8665 ±0.0095	0.2745 ±0.0065	0.4030 ±0.0040
PJFNN	0.1665 ±0.0125	0.0225 ±0.0005	0.0520 ±0.0030	0.2695 ±0.0075	0.0265 ± 0.0005	0.0740 ±0.0020	0.3725 ±0.0055	0.0295 ±0.0005	0.0935 ±0.0005
BPJFNN	0.2363 ±0.0021	0.0303 ±0.0005	0.0727 ±0.0005	0.3490 ±0.0024	0.0350 ±0.0008	0.0970 ±0.0008	0.4370 ±0.0033	0.0373 ±0.0005	0.1140 ±0.0008
BTR	0.1460 ±0.0036	0.0203 ±0.0005	0.0463 ±0.0012	0.2553 ±0.0048	0.0243 ±0.0005	0.0693 ±0.0012	0.3563 ±0.0042	0.0273 ±0.0005	0.0887 ±0.0009
MV-CoN	0.2335 ±0.0023	0.0821 ± 0.0004	0.1171 ±0.0002	0.3688 ±0.0002	0.0912 ±0.0005	0.1510 ±0.0003	0.5041 ± 0.0020	0.0966 ±0.0004	0.1797 ±0.0001
FESA	**0.7874 ±0.0005**	**0.3854 ±0.0009**	**0.4805 ±0.0008**	**0.9073 ±0.0002**	**0.3939 ±0.0008**	**0.5110 ±0.0007**	**0.9521 ±0.0006**	**0.3957 ±0.0008**	**0.5206 ±0.0007**

Table G1. Results for Evaluating Freelancer Competitiveness

Method	K = 10			K = 20			K = 30		
	HR	MRR	NDCG	HR	MRR	NDCG	HR	MRR	NDCG
Word2vec	0.2380 ±0.0004	0.0770 ±0.0012	0.1143 ±0.0008	0.3893 ±0.0005	0.0872 ±0.0012	0.1522 ±0.0010	0.4889 ±0.0022	0.0912 ±0.0011	0.1734 ±0.0005
BERT	0.1931 ±0.0008	0.0637 ±0.0002	0.0933 ±0.0001	0.3537 ±0.0008	0.0747 ±0.0003	0.1337 ±0.0003	0.4901 ±0.0013	0.0801 ±0.0003	0.1626 ±0.0004
GloVe	0.2142 ±0.0003	0.0696 ±0.0005	0.1029 ±0.0002	0.3569 ±0.0007	0.0792 ±0.0003	0.1386 ±0.0003	0.4790 ±0.0013	0.0841 ±0.0003	0.1645 ±0.0001
FESA	**0.7874 ±0.0005**	**0.3854 ±0.0009**	**0.4805 ±0.0008**	**0.9073 ±0.0002**	**0.3939 ±0.0008**	**0.5110 ±0.0007**	**0.9521 ±0.0006**	**0.3957 ±0.0008**	**0.5206 ±0.0007**

Table G2. Results for Alternative Skill Embedding Methods

Method	One Skill		Three Skills		Five Skills		Ten Skills	
	Gini	Entropy	Gini	Entropy	Gini	Entropy	Gini	Entropy
SkillPop	0.9994	0.0000	0.9982	1.5849	0.9970	2.3219	0.9940	3.3219
Apriori	0.9993	0.0000	0.9980	1.5851	0.9967	2.3220	0.9935	3.3219
SVD	0.9993	0.0000	0.9982	1.5594	0.9967	2.3324	0.9935	3.3304
Greedy	0.9801	4.5586	0.9558	5.8187	0.9403	6.2062	0.9668	5.0723
Skillrec	0.9775	5.4880	0.9699	5.8715	0.9638	6.1284	0.9511	6.5670
Bayesian	0.9675	6.0804	0.9331	7.1405	0.9112	7.4570	0.8669	8.1444
FESA-Explore	0.9746	5.6884	0.9661	6.1106	0.9633	6.2303	0.9619	6.2848
FESA-Exploit	**0.9346**	**6.7784**	**0.9101**	**7.2494**	**0.8929**	**7.5441**	**0.8021**	**8.5827**

Table G3. Results for Skill Advice Diversity Analysis

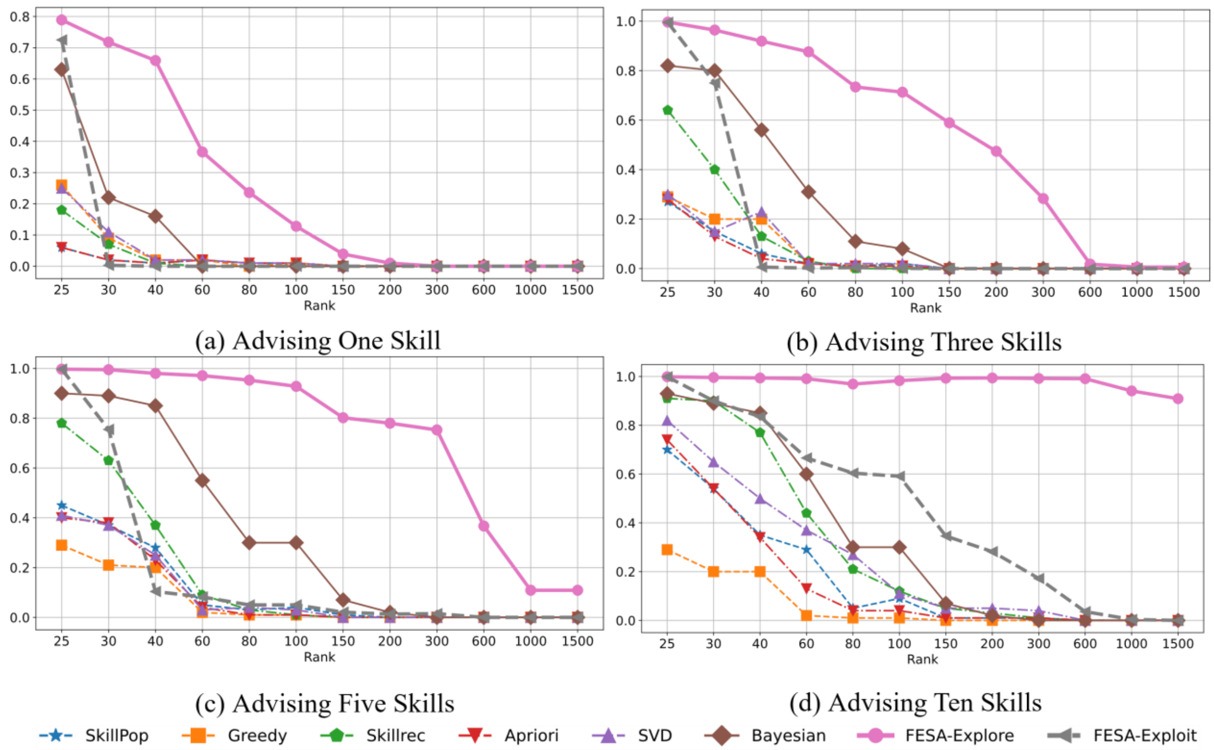

Figure G1. Skill Advising Success Rates

Online Appendix H: Sample Screenshots of the User Interface Used by the Experiment

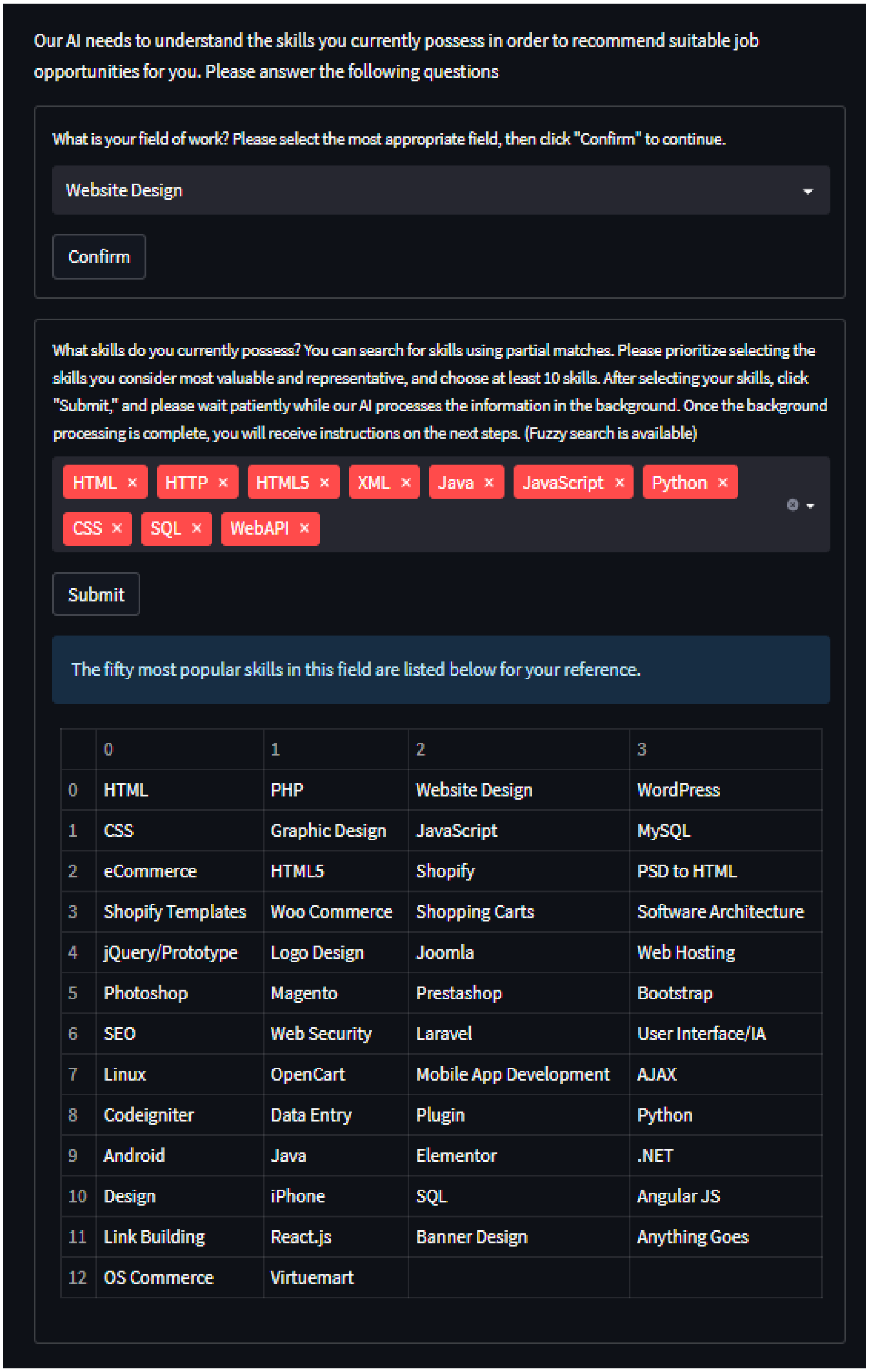

Figure H1. Interface for Participants to Input Their Skillset

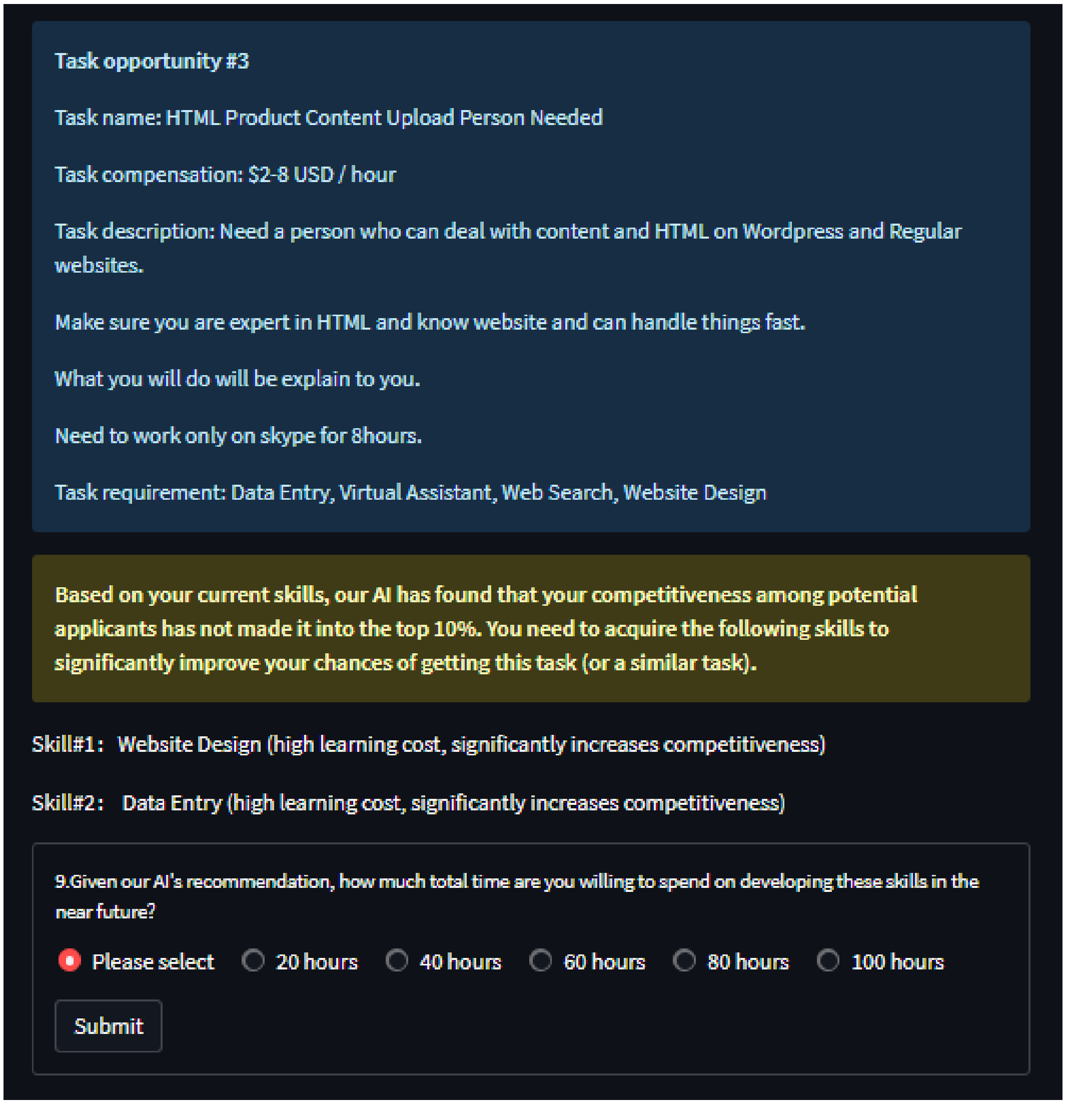

Figure H2. Interface for Participants to Respond Based on Skills Recommended

Online Appendix I: Survey Questions of the Experiment (and English Translations)

GETTING TO KNOW THE PARTICIPANT SECTION

我们的人工智能需要了解您现在掌握的技能，以便于为您推荐工作机会。请回答以下问题。
Our AI needs to understand the skills you currently possess in order to recommend suitable job opportunities for you. Please answer the following questions.

1. 您所从事的工作领域是？请选择最合适的领域，然后点击“确认”继续。
What is your field of work? Please select the most appropriate field, then click “Confirm” to continue.

2. 您现在掌握的技能有哪些？您可通过部分匹配的方式检索技能，请优先选取您认为最有价值和最具代表性的技能，至少选择 10 个技能。选择完技能后，点击“提交”，然后请耐心等待我们的人工智能进行后台处理。后台处理结束后，会有下一步指示。（可进行模糊搜索）
What skills do you currently possess? You can search for skills using partial matches. Please prioritize selecting the skills you consider most valuable and representative, and choose at least 10 skills. After selecting your skills, click “Submit,” and please wait patiently while our AI processes the information in the background. Once the background processing is complete, you will receive instructions on the next steps. (Fuzzy search is available)

CHOOSING A TASK OPPORTUNITY SECTION

根据您所提供的信息，我们的人工智能为您找到了以下三个兼职工作机会。请仔细查看这些在招职位的描述和要求，然后选择您最感兴趣的一个。
Based on the information you provided, our AI has found the following three task opportunities for you. Please review the descriptions and requirements of these opportunities carefully, then select the one you are most interested in.

工作名称 1	Task name 1
工作报酬 1	Task compensation 1
工作描述 1	Task description 1
工作技能要求 1	Task requirement 1
工作名称 2	Task name 2
工作报酬 2	Task compensation 2
工作描述 2	Task description 2
工作技能要求 2	Task requirement 2
工作名称 3	Task name 3
工作报酬 3	Task compensation 3
工作描述 3	Task description 3
工作技能要求 3	Task requirement 3

请选择您最感兴趣的兼职工作。
Please select the task opportunity you are most interested in.

在上一页中，我们的人工智能为您推荐了三个兼职工作机会。您对这组推荐是否满意？
On the last screen, you were presented with three task opportunities. How satisfied are you with this set of task opportunities?

1 – 非常不满意	2	3	4	5	6	7 – 非常满意
1 – Not satisfied at all	2	3	4	5	6	7 – Extremely satisfied

SKILL RECOMMENDATION SECTION

To manipulate ranking information availability (available vs. unavailable):

[***Information available condition manipulation***
根据您现有的技能，我们的人工智能发现您的竞争力在潜在求职者中竟然未能跻身前 10%。您需要掌握以下技能，才能显著提高获得这份兼职工作（或类似兼职工作）的机会。
Based on your current skills, our AI has found that your competitiveness among potential applicants has not made it into the top 10%. You need to acquire the following skills to significantly improve your chances of getting this task (or a similar task).]

[***Information unavailable condition manipulation***
根据您现有的技能，我们的人工智能发现您需要掌握以下技能，才能显著提高这份获得兼职工作（或类似兼职工作）的机会。
Based on your current skills, our AI has found that you need to acquire the following skills to significantly improve your chances of getting this task (or a similar task).]

To manipulate reskilling advice (exploration vs. exploitation):

[***Exploration reskilling advice condition manipulation***
- 技能 1 (较大学习成本, 大幅提高竞争力)
  Skill 1 (high learning cost, significantly increases competitiveness)

- 技能 2 (较大学习成本, 大幅提高竞争力)
  Skill 2 (high learning cost, significantly increases competitiveness)]

[***Exploitation reskilling advice condition manipulation***
- 技能 1 (较小学习成本, 小幅提高竞争力)
  Skill 1 (low learning cost, incrementally increases competitiveness)

- 技能 2 (较小学习成本, 小幅提高竞争力)
  Skill 2 (low learning cost, incrementally increases competitiveness)

- 技能 3 (较小学习成本, 小幅提高竞争力)
  Skill 3 (low learning cost, incrementally increases competitiveness)

- 技能 4 (较小学习成本, 小幅提高竞争力)
  Skill 4 (low learning cost, incrementally increases competitiveness)

- 技能 5 (较小学习成本, 小幅提高竞争力)

Skill 5 (low learning cost, incrementally increases competitiveness)

- 技能 6 (较小学习成本, 小幅提高竞争力)
  Skill 6 (low learning cost, incrementally increases competitiveness)]

DEPENDENT MEASURES SECTION

根据我们人工智能的建议，您近期愿意投入总共多少时间来学习这些技能？
Given our AI's recommendation, how much total time are you willing to spend on developing these skills in the near future?

20 小时	20 hours
40 小时	40 hours
60 小时	60 hours
80 小时	80 hours
100 小时	100 hours

您在上一页面表明，近期愿意投入总共[ ] 小时学习新技能，从而提高获得这份兼职工作（或类似兼职工作）的机会。对于以下每项技能，您近期愿意分配多少小时来学习它？
On the previous page, you indicated that you are willing to spend a total of [ ] hours on developing new skills in the near future to improve your chances of getting this task (or a similar task). How many hours are you willing to devote to each of the following skills?

技能 X	______ 小时
Skill X	______ hours

根据您现有的技能和工作资历，您认为以下技能有多适合您？
Based on your current skills and work experience, how well do you think the following skills suit you?

技能 X	1 – 非常不适合	2	3	4	5	6	7 – 非常适合
Skill X	1 – Not suitable at all	2	3	4	5	6	7 – Extremely suitable

您认为以下技能对您获得您喜欢的兼职工作有多大用处？
How useful do you think the following skills would be for obtaining tasks you desire?

技能 X	1 – 没有任何用	2	3	4	5	6	7 – 非常有用
Skill X	1 – Not useful at all	2	3	4	5	6	7 – Extremely useful

假设您打算申请这份兼职工作（或类似的兼职工作），您会试图掌握以下技能的可能性有多大？
Assuming you intend to apply for this task (or a similar task), how likely are you to try to acquire the following skills?

技能 X	1 – 没有任何可能	2	3	4	5	6	7 – 非常有可能
Skill X	1 – Not likely at all	2	3	4	5	6	7 – Extremely likely

在本次调研中，我们的人工智能是否以下列形式展示了您在潜在求职者中的相对位置？
In this survey, did our AI show your relative position among potential job candidates in the following ways?

- 是　Yes
- 不是　No

在本次调研中，我们的人工智能曾建议您学习几个新技能？
In this survey, how many new skills did our AI suggest that you learn?

- 1-2
- 3-4
- 5+

性别：
Gender:

- 男　Male
- 女　Female
- 其他，请说明：_________　Other, please specify: _________

出生年份：_________
Year of birth: _________

APPENDIX REFERENCES

Abhinav K, Bhatia GK, Dubey A, Jain S, Bhardwaj N (2020) TasRec: a framework for task recommendation in crowdsourcing. *Proc. 15th Int. Conf. Global Software Eng.* 86–95.

Bian S, Chen X, Zhao WX, Zhou K, Hou Y, Song Y, Zhang T, Wen JR (2020) Learning to match jobs with resumes from sparse interaction data using multi-view co-teaching network. *Proc. 29th ACM Int. Conf. Inf. Knowl. Manage.* 65–74.

Dai W, Wang Y, Ma J, Jin Q (2020) BTR: a feature-based Bayesian task recommendation scheme for crowdsourcing system. *IEEE Trans. Comput. Soc. Syst.* 7(3):780–789.

Dave VS, Al Hasan M, Zhang B, AlJadda K, Korayem M (2018) A combined representation learning approach for better job and skill recommendation. *Proc. 27th ACM Int. Conf. Inf. Knowl. Manage. (CIKM)*:1997–2006.

Decorte JJ, Van Hautte J, Demeester T, Develder C (2024) SkillMatch: Evaluating Self-supervised Learning of Skill Relatedness. *arXiv preprint arXiv*:2410.05006.

Gandhi S, Nagesh R, Das S (2022) Learning skills adjacency representations for optimized reskilling recommendations. *2022 IEEE Int. Conf. Big Data (Big Data)*. (IEEE), 2253–2258.

Garneau N, Leboeuf JS, Lamontagne L (2019) Predicting and interpreting embeddings for out of vocabulary words in downstream tasks. *arXiv preprint arXiv*:1903.00724.

Ghosh A, Woolf B, Zilberstein S, Lan A (2020) Skill-based career path modeling and recommendation. *2020 IEEE Int. Conf. Big Data (Big Data).* (IEEE), 1156–1165.

Guan Z, Yang JQ, Yang Y, Zhu H, Li W, Xiong H (2024) JobFormer: skill-aware job recommendation with semantic-enhanced transformer. *ACM Trans. Knowl. Discov. Data* 19(1):1–20.

Han X, Zhu C, Hu X, Qin C, Zhao X, Zhu H (2024) Adapting job recommendations to user preference drift with behavioral-semantic fusion learning. *Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Min.* 1004–1015.

Hossain MS, Arefin MS (2019) Development of an Intelligent Job Recommender System for Freelancers using Client’s Feedback Classification and Association Rule Mining Techniques. *J. Softw.* 14(7):312–339.

Khodak M, Saunshi N, Liang Y, Ma T, Stewart BM, Arora S (2018) A La Carte Embedding: Cheap but Effective Induction of Semantic Feature Vectors. *Proc. 56th Annu. Meet. Assoc. Comput. Ling. (Volume 1: Long Papers)*. 12–22.

Kokkodis M (2021) Dynamic, multidimensional, and skillset-specific reputation systems for online work. *Inf. Syst. Res.* 32(3):688–712.

Kokkodis M, Ipeirotis PG (2021) Demand-aware career path recommendations: A reinforcement learning approach. *Manage. Sci.* 67(7):4362–4383.

Kokkodis M, Ipeirotis PG (2023) The Good, the Bad, and the Unhirable: Recommending Job Applicants in Online Labor Markets. *Manage. Sci.* 69(11): 6969-6987.

Maurya A, Telang R (2017) Bayesian multi-view models for member-job matching and personalized skill recommendations. *2017 IEEE Int. Conf. Big Data (Big Data).* (IEEE), 1193–1202.

Ong XQ, Lim KH (2023) Skillrec: A data-driven approach to job skill recommendation for career insights. *15th Int. Conf. Comput. Autom. Eng. (ICCAE). (IEEE)*, 40–44.

Patel B, Kakuste V, Eirinaki M (2017) CaPaR: A career path recommendation framework. *Proc. 3rd IEEE Int. Conf. Big Data Comput. Serv. Appl. (BigDataService)*. (IEEE), 23–30.

Qin C, Zhu H, Xu T, Zhu C, Ma C, Chen E, Xiong H (2020) An Enhanced Neural Network Approach to Person-Job Fit in Talent Recruitment. *ACM Trans. Inf. Syst.* 38(2): 1-33.

Rosenberger J, Wolfrum L, Weinzierl S, Kraus M, Zschech P (2025) CareerBERT: Matching resumes to ESCO jobs in a shared embedding space for generic job recommendations. *Expert Syst. Appl.* 275:127043.

Sun Y, Ji Y, Zhu H, Zhuang F, He Q, Xiong H (2025) Market-aware long-term job skill recommendation with explainable deep reinforcement learning. *ACM Trans. Inf. Syst.* 43(2):1–35.

Sun Y, Zhuang F, Zhu H, He Q, Xiong H (2021) Cost-effective and interpretable job skill recommendation with deep reinforcement learning. *Proc. Web Conf. 2021*. 3827–3838.

Wang H, Yang W, Li J, Ou J, Song Y, Chen Y (2023) An improved heterogeneous graph convolutional network for job recommendation. *Eng. Appl. Artif. Intell.* 126:107147.

Wu X, Xu T, Zhu H, Zhang L, Chen E, Xiong H (2019) Trend-Aware Tensor Factorization for Job Skill Demand Analysis. *IJCAI*. 3891–3897.

Yuen MC, King I, Leung KS (2021) Temporal context-aware task recommendation in crowdsourcing systems. *Knowl. Based. Syst.* 219:106770.

Zhu C, Zhu H, Xiong H, Ma C, Xie F, Ding P, Li P (2018) Person-job fit: Adapting the right talent for the right job with joint representation learning. *ACM Trans. Manage. Inf. Syst. (TMIS)* 9(3):1–17.