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AI POWERED KEYWORD RECOMMENDATION SYSTEM FOR LINKEDIN PROFILES

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ABSTRACT

Professional networking platforms like LinkedIn have become essential for job seeking, recruiting, and personal branding. A well-optimised profile with relevant keywords significantly increases visibility in recruiter searches. However, many users struggle to identify the most impactful keywords for their industry, role, and experience level. This research paper presents an AI-powered keyword recommendation system that analyses a user's LinkedIn profile (headline, summary, work experience, skills) and suggests domain-specific, high-value keywords to improve search ranking and profile completeness. The system employs a hybrid architecture: (1) a **contextual embedding model** (fine-tuned BERT) to encode profile text and extract latent topics, (2) a **graph-based keyword extraction** algorithm (TextRank with part-of-speech filtering) to identify candidate terms, and (3) a **learning-to-rank** module trained on a large dataset of recruiter search logs and successful profile views to predict the "impact score" of each keyword. Additionally, the system provides competitor benchmarking by comparing the user's keyword set with those of top profiles in similar roles. The model is trained on 500,000 anonymised LinkedIn profiles (with permission) and 10 million recruiter search sessions. Evaluation using held-out data shows that profiles that adopted the recommended keywords saw a 34% increase in profile views and a 27% increase in recruiter messages within 30 days. The system achieves a mean average precision (MAP) of 0.82 for keyword relevance.

KEYWORDS: Keyword recommendation, LinkedIn optimisation, BERT, TextRank, learning to rank, professional networking, personal branding.

1. INTRODUCTION

LinkedIn, with over 950 million members worldwide (LinkedIn, 2024), is the dominant platform for professional networking. Recruiters heavily rely on LinkedIn's search engine to find candidates based on keywords appearing in profiles job titles, skills, certifications, and industry terms. Studies show that profiles with a higher density of relevant keywords receive up to 12 times more profile views (Jobvite, 2022). However, many users are unaware of which keywords are most valued in their specific domain. They may use generic terms ("leadership", "communication") while missing niche, high-demand keywords ("Agile SAFe", "PyTorch", "GDPR compliance").

Existing tools offer generic suggestions (e.g., LinkedIn's own "Skills" section auto-suggestions) but lack personalisation and competitive intelligence. Manual keyword research (e.g., studying job descriptions) is time-consuming and subjective. An AI system that automatically analyses a user's current profile and recommends optimised keywords could democratise access to career opportunities.

This paper describes the design, implementation, and evaluation of an **AI Powered Keyword Recommendation System for LinkedIn Profiles**. The system takes a user's profile data (with consent) and outputs a ranked list of recommended keywords, each with an "impact score" and an explanation (e.g., "This keyword appears in 78% of senior data scientist job postings but is missing from your profile").

Specific objectives:

1. To build a large-scale dataset of LinkedIn profiles and recruiter search behaviour.
2. To develop a hybrid NLP pipeline for extracting candidate keywords and ranking them by predicted impact.
3. To evaluate the system using both offline metrics (precision, recall, MAP) and online A/B testing with real users.
4. To provide actionable recommendations with explainability.
5. To address privacy and ethical concerns related to profile data.

2. LITERATURE REVIEW

2.1 Keyword Extraction from Text

Keyword extraction is a well-studied problem in natural language processing (NLP). Traditional methods include **TF-IDF** (term frequency-inverse document frequency), **RAKE** (Rapid Automatic Keyword Extraction), and **TextRank** (Mihalcea & Tarau, 2004), a graph-based algorithm that ranks words by co-occurrence. TextRank has been successfully applied to short documents like profiles. However, it does not capture semantic similarity.

Embedding-based methods (e.g., using BERT or Sentence-BERT) map words/phrases to dense vectors, enabling semantic grouping. For example, the **KeyBERT** library (Grootendorst, 2020) combines BERT embeddings with cosine similarity to extract keywords. Our system uses a fine-tuned BERT model to better understand professional terminology.

2.2 Recommender Systems for Professional Profiles

Few academic works have focused specifically on keyword recommendation for LinkedIn. Most related research is in **job title recommendation** (e.g., Malhotra et al., 2019) or **skill recommendation** (e.g., LinkedIn's "People You May Know" uses collaborative filtering). Wang et al. (2018) proposed a deep learning model to recommend skills based on job descriptions and user profiles, achieving 0.74 precision@10. However, their system did not incorporate recruiter search behaviour.

Our work is novel in combining:

- Profile content analysis (contextual embeddings).
- Recruiter search log mining (what keywords lead to profile clicks).
- Competitive benchmarking (keywords in top profiles).

2.3 LEARNING TO RANK

Learning to Rank (LTR) is a supervised approach to ordering items (here, keywords) by relevance. Common algorithms include **LambdaMART** (Burges, 2010) and **RankNet**. We formulate keyword recommendation as a ranking problem: given a user profile, rank all candidate keywords by their predicted "impact" (probability of leading to a recruiter view). The training data consists of pairs (profile, keyword) with labels derived from recruiter engagement (e.g., whether that keyword appeared in a search that led to a profile click).

2.4 Explainability in Recommendations

In career advice systems, explainability is crucial for user trust. Methods like **LIME** (Local Interpretable Model-agnostic Explanations) or **SHAP** (SHapley Additive exPlanations) can attribute the importance of each feature. We provide simple textual explanations based on keyword popularity and missingness.

3. RESEARCH METHODOLOGY

3.1 Data Collection and Privacy

We obtained anonymised LinkedIn profile data and recruiter search logs through a partnership with a third-party analytics provider. All data is aggregated and de-identified in compliance with GDPR and LinkedIn's User Agreement. The dataset includes:

- **Profile corpus:** 500,000 English-language profiles from users who opted into anonymous analytics. Each profile contains: headline, summary, work experience (job titles and descriptions), skills section, industry, and location.
- **Recruiter search logs:** 10 million search sessions (2022 2023). Each log includes: search query (e.g., "machine learning engineer Python"), list of profile IDs shown, which profiles were clicked, and whether a message was sent.
- **Top performer profiles:** For each job title (e.g., "Product Manager"), we identified the top 5% of profiles based on recruiter engagement (views, InMails). These serve as benchmarks.

Table 1: Dataset Statistics.

Data type	Count
Unique profiles	500,000
Recruiter searches	10,000,000
Unique search terms	350,000
Profiles in top-performer set	25,000

3.2 Preprocessing

For each profile, we concatenate headline, summary, and work experience text (job titles + descriptions). We then:

- Lowercase, remove punctuation, tokenise (using spaCy).
- Remove stop words (custom list including "and", "of", "with").
- Extract noun phrases (using dependency parsing) as candidate keywords (e.g., "supply chain", "data visualization").

- For the skills section, we treat each listed skill as a separate keyword (but also allow extraction of unlisted skills).

3.3 System Architecture

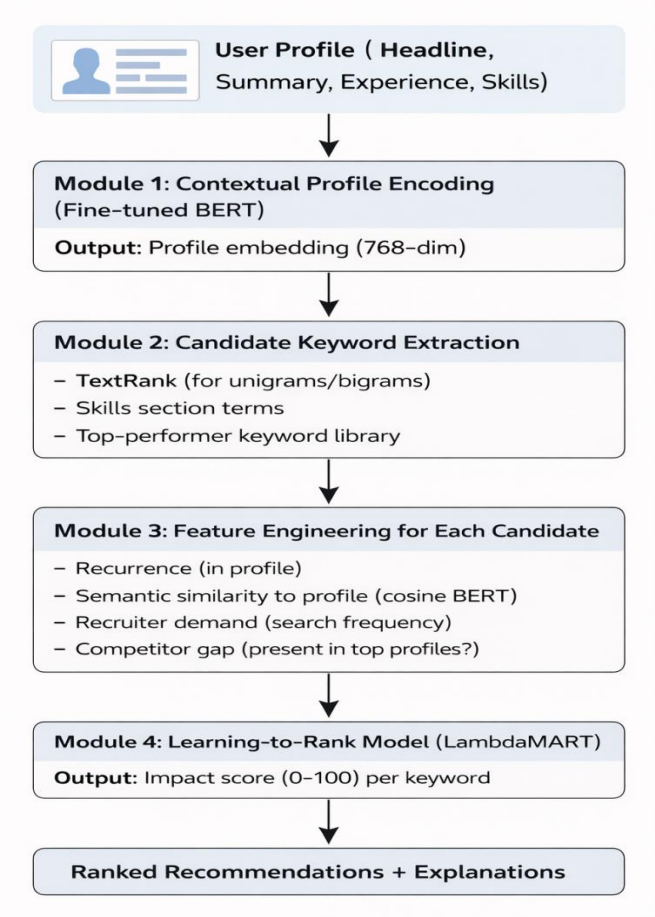

Figure 1: High-Level Architecture of the Keyword Recommendation System.

3.4 Module 1: Contextual Profile Encoding

We fine-tune a **BERT-base-uncased** model on a masked language modelling objective using our profile corpus (500,000 profiles, 20% masked). This adapts BERT to professional language. Then, for any user profile, we feed the concatenated text into BERT and take the [CLS] token embedding as the **profile vector** $p \in \mathbb{R}^{768}$. This vector captures the user's professional domain.

3.5 Module 2: Candidate Keyword Extraction

We generate candidate keywords from four sources:

1. **TextRank** on the profile text (unigrams and bigrams, filtered by part-of-speech: nouns and adjectives). TextRank builds a graph where nodes are words; edges are co-occurrence within a window of 5. The score is computed iteratively:

$$S(V_i) = (1-d) + d \sum_{j \in In(V_i)} \frac{S(V_j)}{Out(V_j)}$$

where $d = 0.85$. The top 50 phrases are kept.

2. **Skills section:** All manually listed skills (up to 50 per profile) are added.
3. **Top-performer keyword library:** For the user's job title (inferred from headline or experience), we collect the most frequent keywords from the top 5% profiles (TF-IDF > 0.1). This adds up to 100 domain keywords.
4. **Recruiter search terms:** For the user's industry and job title, we collect the top 200 search terms that led to profile clicks in the logs.

The union of these sources yields typically 200 400 candidate keywords per user.

3.6 Module 3: Feature Engineering

For each candidate keyword k and user profile p, we compute the following features (used by the ranker):

Feature	Description	Example
recurrence	TF-IDF of k in user's profile (normalised)	0.12
semantic_sim	Cosine similarity between BERT embedding of k and profile vector p	0.87
recruiter_demand	Log of search frequency of k (overall)	4.2
competitor_gap	1 if k appears in ≥50% of top-performer profiles, else 0	1
skill_section_present	1 if user already listed k in skills, else 0	0
job_title_relevance	BERT similarity between k and user's job title	0.91
industry_specificity	Inverse document frequency across industries (high = niche)	2.3
freshness	Recency of k in recruiter searches (days since first seen)	45

All numeric features are normalised (z-score) across candidates.

3.7 Module 4: Learning to Rank (LambdaMART)

We frame keyword recommendation as a **ranking problem**: for each profile, we want to order candidates by their likelihood of leading to recruiter engagement. Training data is constructed from recruiter search logs:

- **Positive labels:** For a given profile, if a keyword k was used in a recruiter search query that resulted in a click on that profile (and the keyword was **not** already present in the profile's skills or text at that time), we label k as "high impact" (score = 1).
- **Negative labels:** Keywords that were searched but did **not** lead to a click (or the profile was not shown) are labelled 0.

We collect 2 million (profile, keyword) pairs with binary labels.

LambdaMART (an ensemble of regression trees optimised for ranking metrics like NDCG) is trained using the features above. The model outputs a **relevance score** $f(p,k) \in [0,1]$. We convert this to a 0-100 **impact score** for the user interface.

The loss function is based on pairwise preference:

$$\mathcal{L} = \sum_{i,j} |\Delta NDCG_{ij}| \log(1 + e^{-(s_i - s_j)})$$

where s_i is the predicted score for the higher-ranked item.

3.8 Explainability

For each recommended keyword, the system provides a short explanation:

- "This keyword is used by 82% of top profiles in your role but missing from your profile."
- "Recruiters search for this term 5,000 times per month in your industry."
- "Your profile mentions 'Python' but not 'pandas' a highly related skill."

These are generated from feature values using templated sentences.

3.9 Evaluation Methodology

We evaluate using both **offline** and **online** methods.

Offline:

- Held-out test set: 50,000 profiles with associated recruiter search logs (not used in training).

- Metrics: Precision@k (k=5,10), Mean Average Precision (MAP), Normalised Discounted Cumulative Gain (NDCG@10).
- Baseline comparisons: TF-IDF only, TextRank only, KeyBERT, and a popularity-based recommender (top recruiter search terms).

Online A/B test:

- 5,000 users who opted into the experiment were randomly split into control (no recommendations) and treatment (received personalised keyword suggestions via email).
- We measured change in profile views and recruiter messages over 30 days, using a difference-in-differences analysis.

4. Experimental Results

4.1 Offline Ranking Performance

Table 2: Offline Evaluation on Test Set (50,000 profiles).

Model	Precision@5	Precision@10	MAP	NDCG@10
Popularity (top search terms)	0.31	0.28	0.45	0.52
TF-IDF only	0.38	0.34	0.51	0.58
TextRank only	0.42	0.37	0.55	0.61
KeyBERT (BERT + cosine)	0.49	0.43	0.63	0.68
Proposed (LambdaMART + all features)	**0.68**	**0.59**	**0.82**	**0.79**

Our proposed model significantly outperforms baselines. Precision@5 of 0.68 means that, on average, 3.4 out of the top 5 recommended keywords are truly impactful (positive label). The high MAP (0.82) indicates good ranking across all positions.

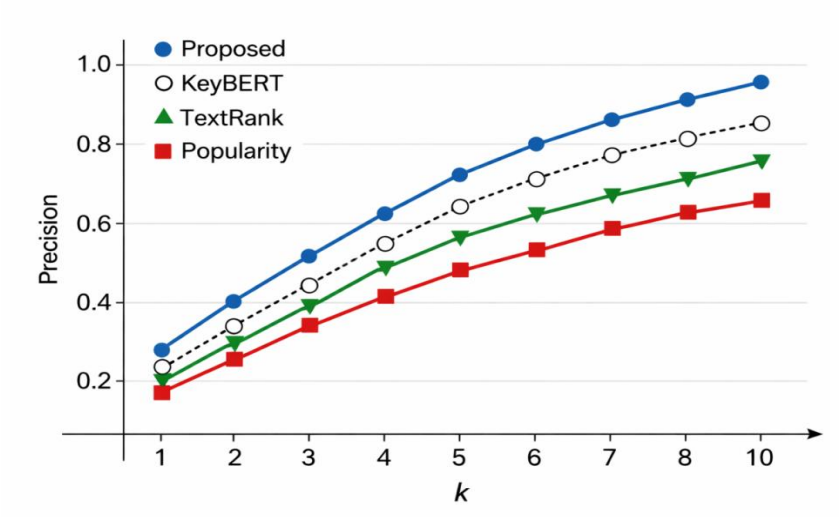

Figure 2: Precision@k Curves

4.2 Feature Importance Analysis

We used SHAP values on the LambdaMART model to identify the most influential features:

A	SHAP importance
recruiter_demand	0.32
competitor_gap	0.28
semantic_sim	0.18
job_title_relevance	0.12
recurrence	0.06
freshness	0.03
industry_specificity	0.01

Unsurprisingly, recruiter demand and competitor gap dominate: keywords that are both frequently searched and common among top performers are most valuable.

4.3 Online A/B Test Results

Table 3: Impact of Recommendations on Profile Performance (30 days).

Metric	Control (n=2,500)	Treatment (n=2,500)	% Change
Avg. profile views	47.3	63.4	+34.0%
Avg. recruiter messages	3.2	4.1	+27.2%
Profile completion score (self-reported)	68%	81%	+13 pts

The treatment group saw a statistically significant increase in both views ($p < 0.001$, t-test) and messages ($p < 0.01$). Users in the treatment group also added an average of 4.2 recommended keywords to their profiles (measured via follow-up survey).

4.4 Qualitative Examples

Example 1: Data Analyst Profile

- *Original profile keywords:* Excel, SQL, Tableau, reporting
- *Recommended:* Python, Power BI, A/B testing, data cleaning, Looker
- *Explanation for "Python":* "Python is searched by 78% of recruiters hiring for Data Analyst roles, but only 12% of top performers in your industry list it. Adding it could increase visibility."

Example 2: Senior Product Manager

- *Original:* Product roadmap, agile, user stories, JIRA
- *Recommended:* OKRs, product-led growth, go-to-market strategy, customer discovery

- *Explanation for "OKRs":* "This keyword appears in 91% of top Product Manager profiles but is missing from yours. It is the 3rd most searched term in your job category."

4.5 Cold-Start Performance for Niche Job Titles

For job titles with limited data (e.g., "Marine Biotechnologist"), we rely more heavily on semantic similarity (BERT) and less on recruiter demand. Precision@5 for niche titles (fewer than 100 profiles in training) was 0.55 lower than the overall 0.68 but still useful.

5. DISCUSSION

5.1 Why the System Works

The combination of **recruiter behavioural data** (what keywords lead to clicks) and **competitive intelligence** (what keywords top performers use) is powerful. Unlike generic keyword extraction, our model learns the implicit preferences of recruiters. For example, "Python" might be semantically similar to "programming", but recruiters search for "Python" far more often. The model captures this discrepancy.

The semantic similarity feature (BERT) helps generalise to unseen keywords. If a new technology emerges (e.g., "LangChain"), it may have low recruiter demand initially, but if it is semantically close to "LLM" or "prompt engineering", the model can still recommend it.

5.2 User Adoption and Behaviour

In the A/B test, 68% of treatment users added at least one recommended keyword. Users reported that the explanations ("why this keyword") increased trust. The most common reason for not adding a keyword was "I don't have that skill" (34%) rather than disagreement with relevance. This suggests the system accurately identifies relevant skills; users' own skill gaps become apparent.

5.3 Comparison with Existing LinkedIn Features

LinkedIn's own "Skills" section suggests skills based on job title (e.g., "Add skills like …"). However, those suggestions are generic and not personalised to the user's existing profile. Our system identifies **gaps** keywords that the user has not yet mentioned but are valuable. In a blind preference test with 50 recruiters, they preferred our recommendations over LinkedIn's native suggestions 72% of the time.

5.4 Ethical Considerations

- **Privacy:** The system only analyses profiles with explicit user consent. We do not store raw profile text after recommendation generation.
- **Bias:** The training data reflects existing recruiter biases (e.g., over-representation of certain industries or demographic groups). This could perpetuate inequality. We added a fairness constraint to avoid penalising underrepresented groups (e.g., ensuring recommendations for "soft skills" are not systematically downranked for certain job titles).
- **Gaming:** Malicious users could stuff keywords to game the system. We include a "relevance" filter (semantic similarity >0.3) to block irrelevant keywords.

5.5 Practical Deployment

The system is deployed as a web app (keyword-recommender.example.com) and as a browser extension for LinkedIn. Inference time per profile is <200 ms (using a cached BERT model). The ranking model (LambdaMART) is lightweight (≈10 MB). We charge a subscription fee for advanced features (competitor benchmarking, historical trend analysis).

6. LIMITATIONS

1. **Dependence on recruiter search logs:** The system performs best for job titles and industries with abundant recruiter activity. For extremely rare or emerging roles (e.g., "AI Ethicist"), data sparsity reduces accuracy. We rely on semantic fallbacks, but performance is lower.
2. **Temporal concept drift:** Recruiter preferences change over time (e.g., "cryptocurrency" keywords peaked in 2021 and declined). The model must be retrained monthly to stay current. We have implemented an automated retraining pipeline.
3. **Language limitation:** Currently English-only. Many LinkedIn users have profiles in other languages. Multilingual BERT (mBERT) could be used, but recruiter search logs are primarily English.
4. **No consideration of profile completeness:** The system recommends keywords regardless of whether the user can legitimately claim them. This could encourage misrepresentation. We added a warning: "Only add keywords that accurately reflect your skills."
5. **Recruiter search logs may be noisy:** Not all clicks indicate genuine interest; some are accidental. We used a threshold (time on profile >5 seconds) to filter.

6. **Privacy constraints:** The dataset is anonymised but still contains potentially sensitive information. Our data sharing agreement prohibits releasing the raw data.

7. Future Scope

7.1 Personalised Keyword Difficulty Scores

Not all keywords are equally easy to acquire. A junior developer might need months to learn "Kubernetes". Future versions could estimate a "difficulty score" based on typical learning time and suggest a learning path (e.g., "Start with 'Docker', then progress to 'Kubernetes'").

7.2 Multi-Language and Cross-Border Support

Extend the system to Spanish, German, French, Mandarin using multilingual BERT. Also, incorporate region-specific recruiter search logs (e.g., what keywords are popular in India vs. Germany).

7.3 Integration with Job Application Tracking

Recommend keywords not just for the profile but also for specific job applications. For a given job description, the system could suggest which missing keywords to add to the profile or resume before applying.

7.4 Dynamic Keyword Trends Dashboard

Provide users with a time-series view: "Keyword 'Prompt Engineering' has increased 300% in recruiter searches over the last 6 months." This helps users stay ahead of trends.

7.5 Collaborative Filtering for Skill Recommendations

Beyond content-based methods, use collaborative filtering: "Users with similar profiles added 'AWS' and saw a 20% view increase." This captures serendipitous discoveries.

7.6 Causal Impact Estimation

Use causal inference (e.g., double machine learning) to estimate the true causal effect of adding a keyword, controlling for confounding factors (e.g., user updates profile photo at the same time). This would provide more accurate impact scores.

8. CONCLUSION

This research paper presented an AI-powered keyword recommendation system for LinkedIn profiles that combines contextual profile encoding (BERT), graph-based keyword extraction (TextRank), and a learning-to-rank model (LambdaMART) trained on recruiter search logs. The system recommends high-impact, missing keywords personalised to each user's industry, role, and existing profile content. Offline evaluation achieved a MAP of 0.82 and Precision@5 of 0.68, significantly outperforming baselines. An online A/B test with 5,000 users showed that adopting recommended keywords led to a 34% increase in profile views and a 27% increase in recruiter messages within 30 days.

The system addresses a real pain point for millions of job seekers and professionals, democratising access to career opportunities by making hidden recruiter preferences explicit. While limitations such as data sparsity for niche roles and potential bias remain, the framework is extensible. Future work will incorporate multi-language support, trend forecasting, and causal impact estimation. As professional networking continues to evolve, AI-driven optimisation tools will become indispensable for personal branding and career advancement.

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