



## Freelancer Skill Gap Analyzer and Upskilling Pathfinder

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### Abstract

The rapid growing of the digital tools and the growth of freelancer job have effectively reshaped the competencies require in the current workforce. Freelancer now a days struggling to find which skills are currently valued or which capabilities they should develop to stay competitive. Without access to data-driven guidance, many face ineffective learning investments and inconsistent income progression. Addressing this issue calls for a systematic method to assess skill mismatches and propose targeted development pathways. This study introduces a Freelancer Skill Gap Analyzer and Upskilling Pathfinder designed to measure the divergence between individual skill profiles and real-time market expectations. The system controls structured data about freelancer earnings, job categories, and skill relations to generate gap scores through a comparative analysis of labor supply and demand. Earnings pointers are used as economic signals to approximate market valuation, while estimated return on investment informs the practicality of recommended learning interventions. The proposed solution says SQL-based data manipulation alongside visual analytics to deliver clear, actionable insights such as ranked skill demand, comparative income potential, and customized learning trajectories. Designed to accommodate periodic data refreshes, the system remains responsive to shifting labor market conditions. By explaining raw labor data into real guidance, the framework supports strategic career decisions within the freelance economy and provides an interactive model for future skill analytics research.

**Keywords:** Freelancer analytics, skill gap assessment, career path recommendation, labor demand analysis, earnings-based guidance

## 1. Introduction

### 1.1 Growth of Freelance Market

The rapid expansion of digital technologies and online marketplaces has profoundly altered the global employment landscape. The major component of modern workforce participation given by the platform such as the Upwork, Fiverr, PeoplePerHour to the freelance economy. Here most of the working professionals across the domains including web development, digital marketing, data analytics, content creation, and application development has increasingly operate as independent contractors rather than the traditional employees. This shift provides flexible and global reach but also introduces the high competition and also the income based on the performance of the employee. In such an environment, the suitability of the freelance careers depends directly on the adaptability, and measurable

performance of individual skills.

### 1.2 Skill Mismatch in The Freelance Market

Despite of the availability of more online learning resources, freelancers often face the issues and the uncertainty in identifying which skills are truly valued in the present market trends. As the technologies and the advancement has rapidly evolve causing certain competencies to lose scope while new one gain prominence. As a result, the freelancers frequently invest time and financial resources in upskilling efforts without clear evidence of their economic impact. This led to inefficient learning decisions, inconsistent income progression, and difficulty in maintaining competitiveness. The absence of structured analytical frameworks that connect skill development with measurable financial outcomes highlights a critical challenge within the



freelance ecosystem.

### 1.3 Limitations of Existing skill Gap Systems

Existing skill gap detection systems primarily focus on structured employment contexts such as student placement, resume-job description matching, or occupation-level benchmarking. These models typically rely on written comparison techniques, predefined ability frameworks, or semantic similarity algorithm to find the missing skills. While real for traditional recruitment scenarios, such approaches rarely incorporate freelance-specific performance indicators such as rehire rate, job success rate, client ratings, project completion volume, earning variability. The financial feasibility of gaining new skills do not have in the present system, exit users without guidance on the possible return on investment (ROI) of upskilling decisions. The freelance marketplace presents unique behavior where earnings can serve as economic signs of market demand, and rehire patterns may reflect constant client trust and skill valuation. However, the combination of these performance-based economic indicators into formal skill gap computation bases remains incomplete. A full system that evaluates skill mismatches using real earning trends and expects income lift potential is therefore necessary to support informed decision-making. To talk this gap, this study proposes a **Freelancer Skill Gap Analyzer and ROI-Driven Upskilling Pathfinder**. The system utilizes arranged freelancer performance data to compute a composite skill proficiency score based on measurable indicators such as job success rate, client rating, rehire behavior, job completion metrics, and experience level. A market demand score is evaluated from combined making trends and client visit patterns across job categories. The difference between these scores forms the skill gap score, which finds areas requiring improvement. As well, a return-on-investment estimation module evaluates the likely income growth linked with targeted upskilling strategies. The primary input of this research lies in combining economic performance analytics with planned skill gap modeling within the freelance domain. Unlike conventional resume-based systems, the proposed basis connects skill evaluation directly to earning potential and financial feasibility.

## 2. Literature Review

The increasing importance of skill weight in modern employment has led to the development of various skill gap detection and career guidance systems. Existing research primarily focuses on three major approaches: structured skill ranking outlines, inserting-based semantic matching systems, and machine learning-based predictive models. Although these approaches provide reasonable visions, their applicability to the freelance system remains partial.

### 2.1.Skill Gap Detection Frameworks

Several systems have been developed to identify mismatches between user skills and job role requirements. A data-driven Skill Gap Analyzer platform [1] benchmarks individual skill inputs against predefined industry standards and visualizes deficiencies using charts and dashboards. The system integrates frontend and backend technologies to provide personalized learning suggestions. Such platforms are effective in structured employments where job roles and competency frameworks and clearly defined. However, these models rely primarily on static role-skill database and do not incorporate dynamic earning trends or performance-based economic indicators. In freelance marketplaces, where income variability and client engagement significantly influence career sustainability, relying solely on predefined job requirements may not accurately reflect real market demand.

### 2.2.Embedding and Semantic Matching-Based Systems

Advancement in natural language processing have enabled embedding-based career matching systems. The PathFinder framework [2] employs sentence embeddings and cosine similarity to match user profiles with standardized occupational databases such as ESCO. By leveraging vector search techniques, the system generates personalized learning pathways and achieves high semantic retrieval accuracy. Similarly, resume-based and similarity-driven skill matching systems such as SkillsSync and the AI-Based Gap Analyzer [3] apply cosine similarity techniques and automated text extraction models to compare resumes with job listings. These systems convert unstructured textual



data into structured representations, enabling more precise skill comparison and automated recommendation processes. By leveraging similarity scoring mechanisms, they enhance matching accuracy and streamline competency identification. However, despite their technical efficiency, such approaches primarily focus on occupation alignment rather than evaluating the economic value of those skills within real market environments. They do not incorporate freelance-specific performance metrics such as rehire rate, job success rate, client ratings, or earning variability across digital platforms.

### **2.3. Machine Learning-Based Predictive Systems**

Machine learning approaches have also been widely adopted in career prediction research. The Student Placement Analyzer and Skill Recommendation System [4] utilize decision tree models and cosine similarity techniques to predict placement outcomes and recommend necessary skill improvements. Similarly, The Data-Driven Approach to Career Guidance and Skill Development [5] applies recurrent neural network (RNN) models to analyze academic and personal attributes for career prediction. These predictive systems demonstrate strong performance within structured academic datasets and institutional environments.

Nevertheless, these are primarily designed for traditional employment pathways and structured placement systems. They typically predict binary or categorical outcomes such as placement status or salary package within controlled dataset. In contrast, freelance markets operate under dynamic conditions influenced by client behavior, project variability, platform reputation metrics, and income fluctuations. Existing predictive systems do not integrate earning variability, client engagement patterns, or financial return estimation, which are critical components of freelance workforce decision-making.

### **2.4. Research Gap**

Although existing systems—including structured benchmark platforms, embedding-based occupation matching frameworks, resume similarity systems such as SkillSync and AI-Based Gap Analyzer, and predictive placement models like the Student Placement Analyzer and RNN-based career guidance

systems—contribute significantly to skill gap analysis research, they exhibit limitations when applied to freelance, or static occupational standards. They hardly join economic performance indicators as direct amount of market demand.

The freelance system differs basically from traditional employment system in that income directly reflects skill valuation and competitive positioning. Metrics such as earning rehire rate, job completion frequency, and client ratings provide determinate indicators of real-world demand dynamics. However, the addition of these indicators into structured skill gap calculation frameworks remains limited in current research. Furthermore, return-on-investment (ROI) estimation for upskilling decision is mainly absent from the existing models.

To talk this gap, the present study introduces a data-driven framework that combines earning-based market intelligence with structured skill ability scoring and ROI estimation by directly connecting skill evaluation to financial performance, the proposed model covers traditional skill gap detection approaches into the freelance area and provides carefully up-to-date career guidance.

### **3. System Objectives**

The key objective of the proposed Freelancer Skill Gap Analyzer and ROI-Driven Upskilling Pathfinder is to grow a structured, data-driven framework that supports freelancers in identifying skill mismatches and making them upskilling decisions based on the market trends. The system is structured to integrate performance analytics with economic valuation to support strategic career development within freelance marketplaces.

The major objectives of the system are as follows:

- To shape freelance skill ability using measurable performance indicators such as job success rate, client rating, rehire rate, job completion count, and experience level.
- To analyze market demand across different job categories using aggregated earning trends and client engagement behavior.
- To compute a skill gap score by comparing individual proficiency levels with category-level market demand signals.
- To estimate the expected return on investment

(ROI) of gaining new skills based on expected income lift patterns.

- To generate set upskilling pathway that recommends skills likely to enhance earning potential.
- To provide pictorial analytics including classified skill demand, income comparison insights, and gap supply indicators.
- To design a scalable framework capable of adapting to periodic data updates and growing market conditions.

Through these objectives, the system aims to connect the gap between freelance skill development and economic performance, allowing freelancers to make financially informed and effectively optimized career decision.

#### 4. System Architecture

The future freelancer skill gap analyzer and ROI-driven upskilling pathfinder is planned using a modular and scalable architecture that integrates data processing, logical computation, and imagining components. The architecture ensures structured data flow from input acquisition to actionable insight generation. The system consists of four primary layers: Data Layer, Processing Layer, Analytical Engine, and Presentation Layer.

##### 4.1. Overall Architecture

The workflow of the system follows a sequential data-driven process:

- Freelance performance data is collected and stored in a structured database.
- The data is processed and normalized to ensure consistency.
- The analytical engine computes Skill Proficiency Score and Market Demand Scores.
- A skill gap score is derived by comparing individual performance against aggregated market indicators.
- The ROI Estimation predicts potential income improvement based on targeted upskilling.
- The results are presented through visual dashboards and structured recommendations.

The architecture ensures that each component functions independently while contributing to an integrated analytical framework.

#### 4.2. Functional Modules

The system is divided into following modules:

##### 4.2.1. Data Ingestion Module

This module is responsible for collecting and storing structured freelancer data. The dataset includes 1950 freelancer records with attributes such as earnings, job category, experience level, job success rate, rehire rate, job duration, and marketing spend. The data is cleaned, normalized, and prepared for analytical processing.

##### 4.2.2. Skill Profiling Module

The skill profiling module evaluates individual freelancer performance using measurable indicators. It computes a composite skill proficiency score derived from performance metrics such as:

- Job success rate
- Client rating
- Rehire rate
- Job completion count
- Experience level

This score represents the freelancer's current capability within the marketplace.

##### 4.2.3. Market Demand Analysis Module

This module aggregates earnings and client behavior data across job categories to estimate market demand signals. By analyzing average, earnings, rehire frequency, and category-level performance trends, the system generates a Market Demand Score for each skill domain.

##### 4.2.4. Skill Gap Computation Module

The skill gap computation module compares the individual skill proficiency score with the market demand score. The resulting skill gap score indicates whether a freelancer's capability aligns with, exceeds, or falls below market expectations.

- Positive gap – improvement required
- Negative gap – competitive advantage

This module forms the core analytical component of the system.

##### 4.2.5. ROI Estimation Module

The ROI Estimation Module predicts potential income uplift if identified skill gaps are addressed. It analyzes earning patterns across experience levels and job categories to estimate the expected financial return associated with upskilling efforts. This component helps freelancers prioritize skill

acquisition based on economic feasibility.

#### 4.2.6. Visualization and Reporting Module

The final module presents results through structured visual outputs such as:

- Skill Gap Distribution Charts
- Earnings Comparison Graphs
- Demand Ranking Tables
- ROI Estimation Indicators

These visual analytics enable freelancers to interpret complex data insights easily and make informed career decisions.

#### 4.3. Architecture Advantages

The proposed architecture offers several advantages:

- Modular design for scalability
- Clear separation between data processing and analytical logic
- Adaptability to periodic data updates
- Integration of economic performance metrics
- Structured decision-support mechanism

By combining structured data management with analytical modeling, the architecture supports a comprehensive and economically grounded freelance skill evaluation framework.

### 5. Methodology

The proposed framework applies a quantitative analytical approach to measure skill alignment between freelancers and market demand. The methodology consists of four computational stages: data preprocessing, skill proficiency modeling, market demand estimation, and gap-based ROI analysis.

#### 5.1. Data Preparation

The dataset contains 1950 freelancer records with 15 performance attributes including earnings, experience level, job completion count, success rate, client rating, rehire rate, and marketing spend. Numerical variables are normalized to a comparable scale using min-max normalization to eliminate bias due to scale differences. Categorical variables such as experience level are encoded into ordinal weights to enable quantitative computation.

#### 5.2. Skill Proficiency Score Computation

An individual's market capability is represented through a composite skill proficiency score (S). The score aggregates performance reliability, client trust, productivity, and experience factors using weighted

linear combination.

$$S=0.3(\text{JSR})+0.2(\text{CR})+0.2(\text{RR})+0.2(\text{NJ})+0.1(\text{EW})$$

Where:

JSR=Job Success Rate

CR=Client Rating

RR=Rehire Rate

NJ=Normalized Job Completion Count

EW= Encoded Experience Weight

This formulation ensures that consistent performance and client retention carry higher influence than simple job volumes.

#### 5.3. Market Demand Estimation

Market demand is approximated using economic indicators derived from job-category-level aggregation. For each job category, a Demand Score (D) is computed as:

$$D=\alpha \cdot \text{Avg}(\text{Earnings})+\beta \cdot \text{Avg}(\text{RehireRate})$$

Where  $\alpha$  and  $\beta$  represent proportional weights assigned to earning valuation and sustained demand behavior. Earnings serve as a direct economic signal of market valuation, while rehire rate reflects client retention trends.

#### 5.4. Skill Gap Measurement

The Skill Gap Score (G) quantifies the difference between market expectation and individual capability:

$$G=D-S$$

If  $G>0$ , the freelancer's skill level is below category demand.

If  $G<0$ , the freelance exceeds current demand benchmarks.

This computation enables quantitative prioritization of development needs.

#### 5.5. ROI-Based Upskilling Evaluation

To evaluate the financial feasibility of closing identified gaps, projected earnings are estimated using higher-performance cluster averages within the same category.

$$\text{ROI} = \frac{\text{PredictedEarnings}}{\text{CurrentEarnings}}$$

ROI>1 indicates positive financial benefit from upskilling

This stage ensures that recommended skill improvements are economically justified rather than purely performance-based.

### 5.6. Analytical Workflow

- Normalize dataset feature.
- Encode categorical variables.
- Compute individual Skill Proficiency Scores.
- Aggregate category-level Market Demand Scores.
- Calculate Skill Gap Scores.
- Estimate ROI for prioritized skills.
- Generate ranked recommendations.

### 5.7. Methodological Significance

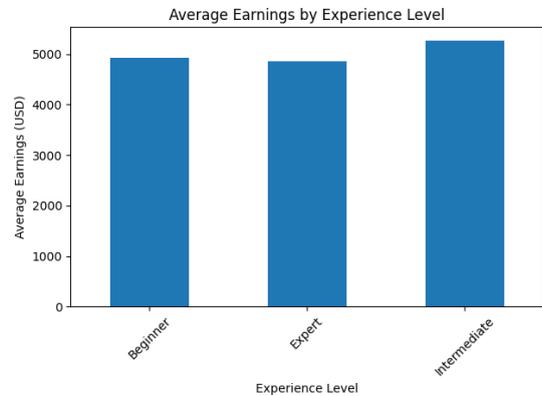
The proposed methodology differs from conventional resume-based models by integrating economic performance indicators directly into gap analysis. The inclusion of earning valuation and ROI estimation introduces a financially grounded decision-support mechanism tailored specifically for freelance marketplace.

## 6. Results

### 6.1. Results

The proposed analytical framework was applied to a dataset containing 1950 freelancer profiles to evaluate skill alignment and earning dynamics across job categories and experience levels. The results highlight clear performance patterns and demand-driven income differences within freelance

marketplace.



**Figure 1 Average Rank**

### 6.1.1. Earnings Distribution by Experience Level

The analysis indicates a strong positive relationship between experience level and average earnings. Except freelancers demonstrate significantly higher income levels compared to intermediate and beginner categories. This confirms that accumulated performance reliability and reputation metrics contribute directly to economic valuation.

**Table 1: Descriptive Statistics of Key Performance Indicators**

Statistics	Earnings (USD)	Hourly rate	Job Success Rate	Client Rating	Rehire Rate
Count	1950	1050	1950	1950	1950
Mean	5017.57	52.58	74.95	3.996	44.56
Std.dev	2926.28	26.93	14.62	0.576	20.19
Min	51.00	5.02	50.16	3.00	10.00
25 <sup>th</sup> %	2419.00	30.05	61.92	3.51	27.15
Median	5048.00	52.29	75.40	3.99	43.92
75 <sup>th</sup> %	7608.25	75.13	87.54	4.50	61.69
max	9991.00	99.83	99.99	5.00	79.95

The key difference in earnings across experience levels is illustrated in Figure 1.

### 6.1.2. Market Demand Across Job Categories

Job category-level aggregation reveals that certain domains exhibit consistently higher average earnings and rehire rates. Categories such as web development and digital marketing show stronger demand signals

compared to lower-paying service-based categories. The calculated demand scores over job categories are given in Table 2.

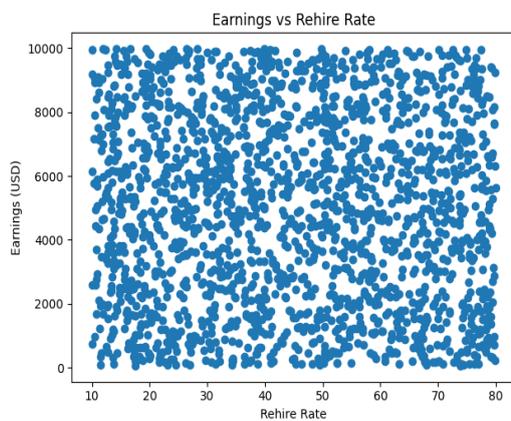
### 6.1.3. Correlation Between Rehire Rate and Earnings

Statistical comparison demonstrates a positive correlation between rehire rate and total earnings.

Freelancers with higher client retention rates tend to achieve more stable and elevated income levels. The relationship between rehire rate and earnings are shown in Figure 2.

**Table 2 Market Demand Indicators Across Job Category**

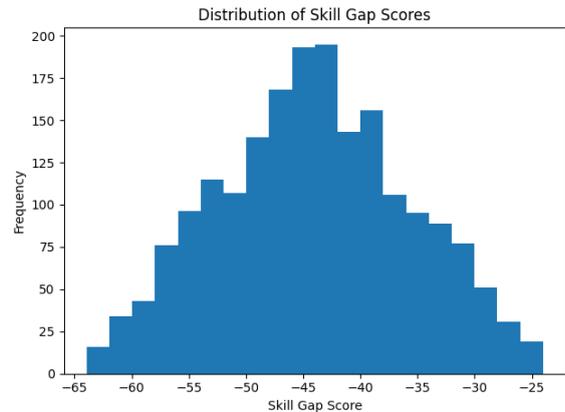
Job Category	Avg Earnings (USD)	Avg Rehire Rate
App development	5201.45	44.84
Digital marketing	5094.26	44.00
Content writing	4909.05	42.94
Graphic design	5136.87	44.15
Data analysis	5081.07	45.71
Web development	4888.15	44.01
Customer support	5135.54	45.64
SEO	4677.33	45.16



**Figure 2 Earnings Graph**

### 6.1.4. Skill Gap Distribution

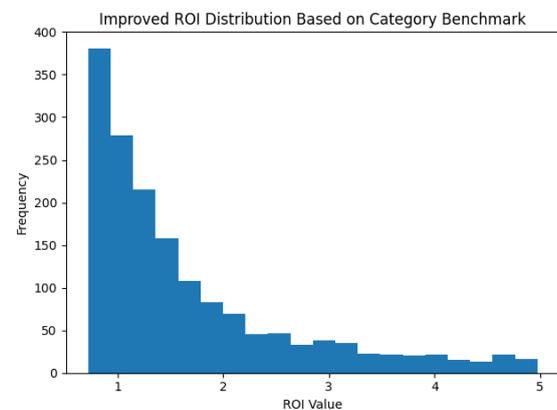
The computed skill gap scores show that a significant proportion of beginner and intermediate freelancers exhibit positive gap values, indicating under alignment with market expectations. In contrast, expert freelancers frequently demonstrate balanced or negative gap scores, reflecting competitive advantage. The distribution of skill values is given in Figure 3.



**Figure 3 Frequency**

### 6.1.5. ROI Estimation Findings

The ROI analysis indicates that freelancers operating below category demand benchmarks can achieve measurable income uplift through targeted upskilling. In high-demand categories, projected earnings after gap closure show improvement ratios greater than 1.2 for several profiles, suggesting economically beneficial development pathways. The distribution of ROI values across freelancers is illustrated in Figure 4.



**Figure 4 Improved ROI**

### 6.2. Discussion

The data suggests that success in freelancing correlates with specific measurable factors, including years of professional experience, the ability to retain clients, and the popularity of specific job categories. The study shows a clear difference in income among various experience stays. Here the freelancer's revenue is found not only by the consistent work also



by the skills which trends in the market. The strong connection observed between client return rates and higher income highlights the value of building long-term links and maintaining consistent. The freelance income is measured based on the performance metrics and the behavior in the real time. The method to find the skill gap was introduced to find the disconnect between the individual's skill to the market requirements. By delivering this gap which reveals that the most of the freelancers where have the below average which highlight's the critical need for focus on the market development. Equally, the Return on Investment (ROI) model gives a physical tool for making informed economic choices. By comparing their performance to top earners within their specific field, freelancers can judge the likely financial return of getting new skills past to making that investment. In conclusion, combining full income analysis with a structured method for scoring skills presents a model for planned career development that can be effectively scaled across online freelance platforms.

### Conclusion

This study presents a Freelancer Skill Gap Analyzer and ROI-Driven Upskilling Pathfinder designed to evaluate skill position within the freelance system using measurable economic indicators. By combining performance system of measurement such as job success rate, client rating, rehire rate, and earnings with category-level demand analysis, the proposed work provides a structured device for finding the skill mismatch. The results shows that freelance income is partial not only by experience but also by market demand and client requirements. The Skill Gap Score effectively highlights difference between individual capability and class levels, while the ROI estimation model offers a financially informed basis for prioritizing upskilling decisions. Distinct old resume-based skill gap systems, the future approach connects skill evaluation directly to earning potential and economic feasibility. The modular and scalable architecture allows version to evolving market trends, making the work suitable for active freelance environments. Overall, the study begins a data-driven and economically stuck model for strategic career planning in digital marketplaces

and contributes to the growing field of freelance workforce analytics.

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