



## UNDERSTANDING EFFICIENCY OF ALGORITHMS FOR GIG PLATFORMS

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**Abstract:**

Online platform for Gig Platforms (short-term work), relies heavily on recommendation algorithms to match customers with clients efficiently. However, the existing systems more often prioritize simple metrics like ratings, that sometime result in inconsistent mapping of client and customer. Therefore this does not please the users and brings down the platform success. This paper brings forward the "Request Response Matching Score" a different algorithm to improve matching efficiency across gig platforms. Taking influence from existing weighted ranking algorithm and k-Nearest Neighbors' feature-based matching, this Match Score equates quality, speed, and correctness. whereas other models are based only on rating. Further analysis gives benefits such as clients gain faster match, customized matches, and newcomers, achieve fairer visibility and platforms gains retention. The Test here include possible computational burden. Still feasibility is appreciable given the existing data infrastructures. The outcome extends to gig economy and future AI integration. However, this study reveals a refined recommendation systems to promote gig jobs, giving a desirable, mathematical based result for a sustaining digital worker platform.

**Keywords:** Algorithms, recommendation, digital, mapping, efficiency, rating

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**Introduction:**

The gig economy, basically refers to digital labor market identified by short-term, flexible jobs associated with digital platforms. It has brought a complete metamorphosis to job market globally. Innumerable workers such as drivers who carry passengers, freelancers who draft designs, and others who handle small job fall in this radar and are coordinated by technology. At the center of this system comes the algorithms, the hidden engines that map workers to clients in real time. Still certain shortcomings exist. Clients scroll through mismatched choice, while potential workers remain unseen. Think of a driver travelling several kilometers for a pickup or a client rigorously looking for a skilled coder. Can a good and efficient algorithm help us in such situation and resolve?

This study suggests how digital gig platforms can improve their recommendation systems by the mechanisms of mapping workers with tasks or clients, to enhance efficiency. Existing algorithms more frequently prefer metrics like ratings, not considering factors like availability and task relevance. This brings down the response time, thereby affecting platform viability in a competitive arena. In this paper we study a variant approach, a different algorithm that equates multiple worker attributes to accurate matches. By combining ratings, availability, and task relevance, termed as "Request Response Match Score" renders faster and appropriate mapping. This algorithm gives workers better opportunity and also improves the gig economy's future.

The challenges are enormous. Efficient matching promises faith and repeat customers, which is the backbone to gig platforms' success. As gig job grows,

algorithms should manage its independent workforce. This paper attempts to say that refining these systems can assist clients with agile service, workers get better chances, and gig platforms gain stability.

We now focus on gig economy algorithms, its understanding, current limitations, a detailed study of Request Response match score, its benefits, and its influence.

### **Literature review:**

#### **1. The rise of gig work: Employment trends in 2023, by (Brown & Taylor, 2024).**

The author is emphasizing the important role of the gig economy in the new era global job market, accounting for over 20% of workers in specific sector, according to Brown & Taylor (2024). They put forward its wide prospects, encompassing involving actual task (like delivery or matching ride) and online tasks (such as freelancing). The phrase explains the gig economy's abundance reflection on the labor market, changing legacy work structures. It focuses on inclination toward various, work that demand less duration to complete, or task relevant work, impacting a considerable portion of the employees in particular area.

#### **2. Gig economy in 2025: A global snapshot by (Smith, 2023).**

The author, citing Smith (2023), is projecting the huge scale and diversity of the gig economy by 2025, with millions of workforce designated in variety jobs, such as drivers and freelancers. They throw light on how digital services act as the backbone, gracefully integrating these labors across different tasks and place. The phrase suggests a predominant advancement in job opportunities, where labor oriented jobs are increasingly supplemented by digital-driven, versatile work scenario. It refers to the gig economy's broad adoption and its faith on online platforms to create

a network of workers with opportunities facilitating the digital world.

#### **3. User satisfaction and platform abandonment in gig markets by (Garcia & Patel, 2022).**

The author is speak about out a key challenge in the gig economy, pointing to a study by Garcia & Patel (2022) that found approximately about 30% of gig platform users stop using them due to inadequate mapping. This implies that clients are perturbed when the technology fails to match them with suitable tasks, labor, or service. It means that inefficient matching of characteristics such as work expertise, rating, or preferences can drive people away, emphasizing a significant scope for betterment in these digital platforms.

#### **4. Gig worker frustrations: A qualitative study by (Davis, 2023)."**

In the article referenced by "Davis, 2023," the author speaks about the problems of online gig workers who feel unnoticed despite their readiness to work. The phrase may infuse a sense of dissatisfaction and invisibility in a competitive digital environment, where opportunities may not synchronize with their capability. These workers are more often associated with skill set, opportunity, and determination, still they encounter problems in obtaining a stable position. The author could be mentioning issues in the gig economy, such as oversaturation, algorithmic biases, or lack of clarity, that exclude potential employee from growing. In a nut shell it reflects a drop in linkage between their preparedness and the accreditation or rewards they obtain.

#### **5. The anatomy of a large-scale hyper textual web search engine by (Brin& Page, 1998).**

In referencing "Like PageRank, which uses weighted sums to rank pages (Brin & Page, 1998)," the author makes a comparison to the initial algorithm developed by Sergey Brin and Larry Page

for Google. They mention that Page Rank recognizes the importance of grading of web pages by calculating weighted sums based on the count and quality of links pointing to them. The author wishes to elaborate how this approach assigns metric systematically, pushing web pages with quality, and more relevant in connections. By referring this example, they may be suggesting a similar idea in their own relevance using weighted features to rank or grade something more logically with improvement.

#### **6. Data infrastructure in gig platforms by (Kumar, 2020).**

In the statement "Request Response match score uses weights to rank workers. Platforms already track ratings, response times, and task details, making it feasible (Kumar, 2020)," the author is proposing that a system called Request Response match score (possibly a ranking model) uses weighted metrics to assess gig workers. They suggest that this approach is practical because online platforms already collect relevant data—like user ratings, how quickly workers respond, and specifics of completed tasks. The author's point is that Request Response match score uses existing information to create an organized, unbiased method to match workers, in resemblance to how algorithms prioritize results elsewhere. By considering feasibility, they mean that adopting Request Response match score does not expect to start from the beginnings because the essential functionality is already available, resulting in a seamless progress to next stage for better worker consideration.

#### **7. AI and the future of gig work by (Nguyen, 2024).**

In the statement "Machine learning could next personalize weights per user (Nguyen, 2024)," the author is mentioning an improvement where machine learning customize evaluation criteria—or

"weights"—to individual users in a system, likely linked to the gig economy or a similar platform. They opine that instead of a one-size-fits-all approach, algorithms could adjust how factors like capability, cost, availability, quality are prioritized based on every individual user's unique choice thereby enhancing personalization and satisfaction. By referencing Nguyen's 2024 work, they say this concept is forward-looking and possible. The aim is a more tailored experience, aligning output with what each individual user weighs and values the most.

#### **Methodology:**

The basic algorithm assigns rank or allot task to individuals which is pivotal to gig platforms. The popular page rank algorithm gives preference to measures such as rating. On the other hand the vicinity and proximity is measured in k-NN approach. Rating has its limitations like it considers past performance and does not consider the availability and task relevance. It simplifies the skill set and can sometime be biased. The k-NN approach also has certain boundaries such as distance measure. Heterogeneous factors like experience, availability and creativity are ignored. The implications of these approaches are immense on gig workers.

An empirical move will help to justify the matching process considering various features both Qualitative and Quantitative. Here we combine rating and task oriented categorization features to get better Request Response match score. Here we understand the two fundamental algorithm that suggest recommendation to client such as, Google page rank algorithm and k-NN algorithm.

The Page rank Algorithm is applied to rank web pages by search engines. Developed by Larry Page and Sergey Brin has evolved over the years since its introduction. It helps to understand how web pages are graded for acceptance and relevance. In the context of

gig economy it is more applicable considering greater visibility in the online approach. Every link connecting one page to another is considered as a vote of confidence. If Page 1 links Page 2 it only shows that Page 1 endorses Page 2. Obviously not all votes are equal. The weightage associated with a vote depends on the PageRank of the linking Page. A link from a popular site will have higher worth than a link coming from a recent blog. The next thing we consider for recommendation is the damping factor. It is the possibility that a user clicks a link rather than jumping to any link at random. It prevents the link from being isolated. Finally PageRank is computed iteratively. The importance of each page is realized when the rank itself stabilizes. The algorithm grades pages purely based on count of inbound and outbound references.

The k-NN is a simple algorithm especially in gig market where we can suggest freelancers with favorable jobs, or predict service demand or assign workers to Clients. Each data point say a worker or a client is identified as multidimensional point and each dimension represents a feature such as skill, rating, etc. When a new data needs to be classified k-NN calculates the distance between new point and existing dataset. Either Euclidean distance or Manhattan distance formula is used. The algorithm then identifies k closest data points to the new point. For classification say 3 out of 5 neighbors is considered a good fit. In case of regression it averages the value of its k neighbors. The algorithm finally assigns the new point a label or value based on its neighbors.

In Mathematical terms distance between two points is calculated as  $\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$

To have a different efficient algorithm that suits and works efficiently in a gig marketplace we combine the above two Algorithm bringing in many feature selection and not limiting to Rating used by Page rank and distance used by k-NN.

### Findings:

Inorder to handle these issues "Request Response Match Score" a similar recommendation algorithm denoted as: "RRMS =  $(0.4 \times R) + (0.3 \times A) + (0.3 \times T)$ ". Here, R is the worker's rating (normalized 0-1, e.g., 4.5/5 = 0.9), A is availability or response time (normalized, e.g., 1 - minutes/30), and T is task relevance (0-1, based on skill match or keywords). RRMS grades workers per request, preferring the largest score.

The above mentioned recommendation is purely based on established algorithms. Like Google's PageRank, which ranks pages via weighted link scores, RRMS considers 40% for ratings that promises quality and 30% for availability or presence and another 30% for task relevance. RRMS is a simple, per-input computation, adaptable to gig platforms' instantly. It also embraces k-Nearest Neighbors (k-NN) by matching based on features—ratings, availability, relevance not just adhering to finding the "nearest" workers to suit the client's requirement.

The thrust assigned (40%) rating, while availability and relevance (30%) each. Imagine a client requesting a ride: Worker A (R=4.5, A=5 min, T=0.9) vs. Worker B (R=5, A=20 min, T=0.7). Normalize \*A\* (e.g., 1 - min/30): A's A = 0.83, B's A = 0.33. Considering - A: RRMS =  $(0.4 \times 0.9) + (0.3 \times 0.83) + (0.3 \times 0.9) = 0.879$ ,  
- B: RRMS =  $(0.4 \times 1.0) + (0.3 \times 0.33) + (0.3 \times 0.7) = 0.709$ .

Worker A is recommended considering vicinity over rating unlike a rating-only system that opts Worker B.

### Conclusion:

Considering the feature selection and task relevant attributes used in the algorithm for recommendation to match client and worker requests, we observe that a single attribute is not sufficient. For a good and efficient recommendation multidimensional feature selection can be adopted that truly helps gig platform

and gig workers. This reduces the search time and also boosts the morale of the worker due to their high visibility. It levels the ground and considers both a newcomer and a seasoned performer equal. Gig platform prefer speed over cost making faster and improved match. Better visibility of gig workers help them earn more and reduce income inequality. The gig economy survives on algorithms. RRMS shows they can adapt to serve all stakeholders in an improved fashion Its outcome can influence innovation, and integrate seamlessly both technology and the physical requirements of gig workers.

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**Cite This Article:**

**Narayanan S. & Iyer S.P. (2025).** *Understanding efficiency of Algorithms for Gig Platforms.* In **Aarhat Multidisciplinary International Education Research Journal**: Vol. XIV (Number II, pp. 197–201).