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HYBRID JOB RECOMMENDATION MODEL INTEGRATING TF-IDF, SBERT, AND WEIGHTED SCORING SYSTEM

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ABSTRACT

The recent breakthroughs, particularly transformer-based models brought a significant improvement in job recommendation systems. These models are semantic-based. However, this type of approach can still be improved. The proposed hybrid job recommendation model integrates Term Frequency-Inverse Document Frequency (TF-IDF), Sentence Bidirectional Encoder Representations Transformers (SBERT) model, and a weighted scoring system, which comprises a semantic boost and skill gap penalty to achieve a more comprehensive and contextual recommendation process. In contrast to models that treat all candidate features uniformly, this system assigns distinct weights to attributes like skills, experience, and education through a weighted scoring system. It also integrates a semantic boost, which considers the clustering of terms and recency of expertise. The hybrid job recommendation system also includes the skill gap penalty, which is used to reduce scores when essential skills listed in a job description are missing from the candidate's profile. The 1.0 score of both Normalized Discounted Cumulative Gain (NDCG) and Mean Average Precision (MAP) signifies that the scoring underlying features and the logic used are highly effective in identifying and prioritizing relevant job opportunities for your profile within this dataset.



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I. INTRODUCTION

As online job postings and applicant profiles expand rapidly in both scale and complexity, there is an increasing demand for more sophisticated recommendation systems that can effectively connect employers and job seekers [1]. Such systems seek to enhance recruitment by intelligently linking candidate profiles with relevant job descriptions. However, keyword-driven approaches frequently yield limited or inaccurate matches between required and actual qualifications. These limitations persist as keyword-based algorithms lack the capacity to differentiate feature importance or to recognize semantic relations between profiles and job descriptions. Moreover, such methods lack semantic comprehension, making them vulnerable to ambiguous terminology [2]. Furthermore, many conventional models continue to rely on keyword matching or basic similarity measures, representing job descriptions as undifferentiated text blocks [3]. Recent NLP breakthroughs, particularly transformer-based models, have empowered job-matching systems to capture semantic nuances beyond surface-level keyword similarity. To mention, these are: BERT, RoBERTa, DistilBERT, GPT-4.0, Gemini, and Llama. These models are semantic-based. This means it understands the semantics between words. This is a very important development in the recommendation system [4], [5]. However, this type of approach can still be improved. By [6] aims to improve the candidate career-matching process for the human resource (HR) department by implementing automation, machine learning (ML), and natural language processing (NLP) techniques are applied to infer and analyze comparative semantic resume attributes. In this study, the ranking support vector machine (RankSVM) algorithm is applied to rank the resumes based on the attributes. In turn [7] proposed a Graph-based Person-Job Fit Neural Fusion (GPJFNNF) model for accurate person-job fit for an intelligent recruitment system. The GPJFNNF model used a pre-trained BERT-based model to effectively capture the sentence embedding semantic information of job and resume texts. According to [8] utilizes all-MiniLM-L6-V2, an SBERT pre-trained model. According to this study, the model showed exceptional performance across different Top-K accuracy metrics, underscoring its robustness in identifying suitable applicants from a vast pool of embedding models using cosine similarity.

By [9] study, an online recruitment application is presented that integrates semantic similarity and Artificial Intelligence (AI) to improve candidate matching. It proposed a system that leverages natural language processing (NLP) techniques such as TF-IDF vectorization, cosine similarity scoring, and domain-specific keywords weighting to interpret conceptual relevance between resumes and job descriptions, enabling more accurate and inclusive recruitment outcomes. This study also conducted a comparative analysis of TF-IDF versus BERT / SBERT. It concluded that although the embedding based on LLMs may enhance contextual sensitivity, using TF-IDF embeddings is a more pragmatic and responsible approach for a scalable and ethical recruiting system. The proposed framework integrates Term Frequency-Inverse Document Frequency (TF-IDF), Sentence Bidirectional Encoder Representations from Transformers (SBERT) model, cosine similarity, and a weighted scoring system, which comprises weighted section analysis, semantic boost, and skill gap penalty to achieve a more comprehensive and contextual recommendation process. In contrast to models that treat all candidate features uniformly, this system assigns distinct weights to attributes like skills, experience, and education through a weighted section analysis. It also integrates a semantic boost, which considers the clustering of terms and recency of expertise. The hybrid job recommendation system also includes the skill gap penalty, which is used to reduce scores when essential skills listed in a job description are missing from the candidate's profile. By jointly considering the relevance, uniqueness, and contextual significance of candidate attributes, the enhanced system delivers more accurate, fair, and dynamically relevant job-candidate matches, ultimately improving the quality and reliability of employment recommendations. This makes the job recommendation more accurate, and the weight assignment is flexible, allowing it to be changed according to the importance of each attribute.

II. MATERIALS AND METHODS

This section outlines the materials and methodologies employed in developing and evaluating the proposed enhanced job recommendation system.

II.1 DATA COLLECTION AND PREPARATION

II.1.1 User Profile Data

User profiles were provided, containing educational background, skills and competencies, work experience, certifications, and preferred job roles or industries. This data was loaded and processed to extract relevant features.

II.1.2 Job Postings Data

Job postings include job titles, descriptions, types, experience levels, salary ranges, and company information. These postings were transformed into a structured format, segmenting the description into distinct sections such as job_title, description, skills, requirements, location, company, and posting_date. This structured approach facilitated weighted scoring system.

II.2 JOB MATCHER IMPLEMENTATION

The core of the recommendation system is the JobMatcher class, which incorporates several advanced natural language processing (NLP) and machine learning techniques.

II.2.1 Text Preprocessing

All text was converted to lowercase. Non-alphanumeric characters (except spaces) were removed using regular expressions. Standard English stopwords from nltk.corpus.stopwords were used, augmented with a custom list of domain-specific stopwords (e.g., 'job', 'position', 'experience') to focus on more meaningful terms. The SnowballStemmer from NLTK was applied to reduce words to their root form.

II.2.2 Feature Extraction

A TfidfVectorizer was used to convert preprocessed text into numerical feature vectors. The key parameters included:

ngram_range=(1, 3): To capture unigrams, bigrams, and trigrams.
max_features=7500: Limiting the number of features to the most frequent.
stop_words='english': Utilizing built-in English stopwords.
min_df=2: Requiring terms to appear in at least two documents.
use_idf=True and sublinear_tf=True: For advanced term weighting.

The SentenceTransformer ('all-MiniLM-L6-v2') model was employed to generate dense, semantically rich embeddings for both user profiles and job postings. Raw, minimally processed text was used for SBERT to leverage its contextual understanding capabilities.

II.2.3 Novelty-Enhanced Scoring Factors

Skill Rarity Index: A custom index was built by extracting key terms from all job descriptions and calculating the inverse frequency of each term, assigning higher weights to rarer skills. **Semantic Skill Clustering:** Predefined clusters of related skills (e.g., 'programming', 'data_science', 'networking_fundamentals') were used to provide a boost to terms falling within these clusters, indicating a stronger thematic match.

Recency Weighting: The calculate_recency_weight function applied a time-decaying boost to skills and terms mentioned in more recent work experience, emphasizing up-to-date relevance.

Position Importance Weighting: Different sections of a job posting (e.g., 'job_title', 'skills', 'requirements', 'description', 'company') were assigned varying importance weights, influencing the overall contribution of terms from these sections to the final TF-IDF representation.

II.2.4 Recommendation Generation

Combined Similarity Calculation: The final base similarity score was a weighted combination of TF-IDF cosine similarity (50%) and SBERT cosine similarity (50%), balancing keyword-based and semantic matching.

Score Adjustments: The base similarity was further refined by applying a skill_gap_penalty for critical skills missing in the user's profile and a semantic_boost derived from skill clustering and recency factors.

Top-N Recommendations: Job postings were ranked based on their final match scores, and the top N recommendations were returned.

II.3 EVALUATION METRICS

To assess the performance of the recommendation system, the following evaluation metrics were used:

Mean Average Precision (MAP): Evaluates the ranking quality by averaging the precision at each relevant item in the ranked list.

Normalized Discounted Cumulative Gain (NDCG@k): Measures the ranking quality considering the graded relevance of items and their positions in the ranked list, up to k items. Hypothetical ground truth relevance scores were assigned based on final match scores for demonstration purposes (e.g., scores ≥ 60 as highly relevant, ≥ 40 as moderately relevant, otherwise low relevance).

II.4 VISUALIZATION

Several visualizations were generated to provide insights into the recommendation process:

Job Recommendation Score Breakdown: A bar chart visualizing the contribution of combined base score, semantic boost, and skill gap penalty to the final score for each recommended job.

TF-IDF Matrix Heatmap: A heatmap displaying the TF-IDF values for the top 30 most important features across the user profile and recommended job postings.

Cosine Similarity Matrix Heatmap: A heatmap showing the pairwise cosine similarity between the user profile and recommended jobs based on TF-IDF vectors.

Term Contribution Heatmap: For the top recommended job, a heatmap illustrating the TF-IDF score, skill cluster boost, recency boost, and total contribution for key terms.

III. RESULTS AND DISCUSSIONS

The system produces job recommendations by analyzing candidate-supplied profile data, including education, work history, skills, certifications, and stated job preferences. This data is processed and analyzed to match candidates with suitable job openings. The system evaluates the candidate's qualifications, such as degrees, relevant job experience, language skills, and industry certifications, alongside their job preferences, including location, salary expectations, and desired job role. Using this data, the system identifies job opportunities that align with the candidate's profile, ensuring that the recommended positions are both relevant and realistic. The results of this process provide a set of personalized job recommendations, which reflect the candidate's skills, experience, and aspirations, maximizing the chances of a successful job match.

III.1 ACCEPT PROFILE DATA AND JOB POSTING

Candidate profile data—covering skills, experience, education, and preferences—was collected, along with structured job postings detailing required qualifications and salary information. This data was stored and processed to ensure that both candidate profiles and job postings were ready for analysis. The employer for job postings inputs the following but not limited to:

- Location
- Salary Range
- Job Description
- Skills/Qualifications

The candidate inputs the following from his professional profile information, including but not limited to:

- Personal details (name, location, contact, employment status)
- Education background in culinary arts
- Professional certifications and training
- Work experience as a Sous Chef and Line Cook
- Language proficiency in English and Albanian
- Culinary skills

Junior Chef (International Cuisine)

Location: Albania

Salary Range: \$43,000 - \$55,000

Experience Level: Junior

Job Type: Full-Time

Vacancies: 2

Expiration Date: April 6, 2025

Job Description: Looking for a talented Chef with expertise in menu development, food preparation, and kitchen management. Responsibilities include creating innovative dishes, managing kitchen staff, and ensuring high-quality food standards.

Required Skills:

- Experience with various international cuisines
- Knowledge of food safety regulations
- Menu Planning
- Food Presentation
- Kitchen Management

Pastry Chef

Location: Tirana, Albania Salary Range: \$38,000 - \$48,000

Experience Level: Entry-Level

Job Type: Full-Time

Vacancies: 1

Expiration Date: April 15, 2025

Job Description: A leading restaurant chain seeks a Pastry Chef specialized in European desserts. Responsibilities include creating daily dessert menus, preparing high-quality pastries, training junior kitchen staff, and ensuring product quality standards.

Required Skills:

- European dessert expertise
- Cake Decoration
- Chocolate Work
- Bread Making
- Knowledge of traditional Albanian pastries (preferred)

Food and Beverage Manager

Location: Durrës, Albania

Salary Range: \$45,000 - \$60,000

Experience Level: Mid-Level

Job Type: Full-Time

Vacancies: 1

Expiration Date: April 20, 2025

Job Description:

An upscale hotel seeks a Food and Beverage Manager to oversee all F&B operations. Responsibilities include managing restaurant and catering services, developing menus with the executive chef, controlling inventory and costs, and ensuring compliance with health and safety regulations.

Required Skills:

- Experience in hospitality management
- Staff Management
- Inventory Control
- Customer Service
- Excel proficiency

Figure 1: Example of Job Postings.

Source: Author, (2026).

Name: Mr. Marco Antonio Rossi
 Location: Divjakë, Albania
 Contact: +355691234567
 Employment Status: Unemployed | Actively looking for work | Willing to start immediately
 Job Preference: Chef in Food Service industry (Preferred location: Divjakë, Albania)
 Salary Expectation: 45,000 – 55,000

Education

Bachelor of Science in Culinary Arts
 Culinary Institute of Manila | 2018 – 2022

Certifications & Training

Certified Executive Chef – European Culinary Federation (Valid until July 2027)
 Certified Professional Chef – Advanced Culinary Techniques
 International Culinary Academy | 120 hours
 Skills: Molecular Gastronomy, International Cuisine
 Food Safety Manager – Food Safety and Sanitation
 Food Safety Institute | 40 hours
 Skills: HACCP Implementation, Sanitation Procedures

Work Experience

Sous Chef – Le Petit Bistro, Paris, France
 Aug 2022 – Dec 2024 (Full-Time)
 Line Cook – Trattoria Milano, Rome, Italy
 Jun 2020 – Jul 2022 (Full-Time)

Language Proficiency

English – Fluent (Read, Write, Speak, Understand)
 Albanian – Fluent (Read, Write, Speak, Understand)

Skills

- Menu Development
- Food Presentation
- Kitchen Management
- Food Preparation

Figure 2: Example of Candidate Profile Data.
 Source: Author, (2026).

Based on example profile data and the available job postings, the algorithm should display the following recommended jobs where N-recommendations = 3:

- Junior Chef (International Cuisine)
- Food and Beverage Manager
- Pastry Chef

```
Job: Junior Chef (International Cuisine)
Match Score: 65.9%

Job: Food and Beverage Manager
Match Score: 37.8%

Job: Pastry Chef
Match Score: 29.1%

Job: Research Scientist - Pharmaceutical
Match Score: 16.1%

Job: Civil Engineer
Match Score: 13.6%

Job: Full Stack Developer
Match Score: 10.9%
```

Figure 3: Recommendation Result using enhanced TF-IDF + SBERT + Weighted Scoring.
 Source: Author, (2026).

The job matching algorithm identified the Junior Chef position for international cuisine as an optimal fit for the candidate's background. The position not only matches his salary expectations and desired location within Albania, but also directly calls for his core competencies in menu development, food presentation, and kitchen management. His experience working in French and Italian restaurants provides precisely the international cuisine exposure the employer seeks. The Food and Beverage Manager (2nd recommended job) role presents an opportunity for career advancement, leveraging the candidate's kitchen expertise while expanding into broader hospitality management. The Pastry Chef position (3rd recommended job) represents a potential specialization path within the candidate's culinary career. While not explicitly mentioned in his experience, his formal training likely included pastry fundamentals that could be expanded upon in this role. The remaining positions (Civil Engineer, Full Stack Developer, and Research Scientist) show no meaningful alignment with the candidate's background and were correctly filtered out by the recommendation system.

Table 1: Score Breakdown of the recommendation results using the enhanced recommendation approach.

Job Title	TF-IDF-based Similarity Score	SBERT base Similarity Score	Combined base Score	Semantic Boost	Skill Gap Penalty	Final Score
Junior Chef (International Cuisine)	63.93	57.64	60.79	1.11	4.13	67.19
Food and Beverage Manager	23.34	48.39	35.86	1.08	6.28	37.81
Pastry Chef	8.63	39.73	24.18	1.23	6.86	29.49
Research Scientist - Pharmaceutical	3.24	26.75	15.00	1.10	7.46	16.27
Civil Engineer	6.86	19.69	13.28	1.05	6.43	13.77
Full Stack Developer	8.61	13.74	13.28	1.00	7.78	11.00

Source: Author, (2026).

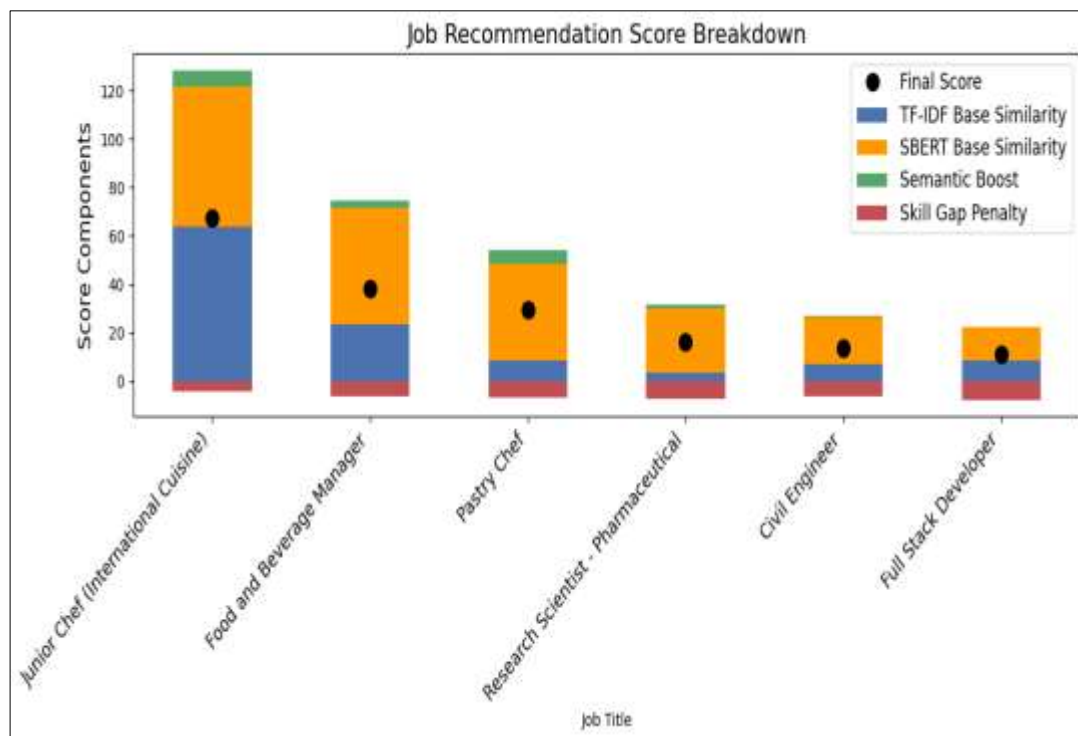


Figure 4: Job Recommendation Score Breakdown.

Source: Author, (2026).

Table 2 and Figure 4 summarize how each job's similarity metrics contribute to the final ranking by combining statistical, semantic, and skill-alignment components. For the role of Junior Chef (International Cuisine), the candidate has a high combined base similarity score of 60.79, indicating a strong match in terms of general qualifications and experience. This is further enhanced by a semantic boost factor of 1.11, suggesting good contextual relevance—perhaps due to experience in international cuisine or a similar culinary domain. Although there is a minor skill gap penalty of 4.13, the match score remains high at 67.19, making this job the top recommendation. In contrast, the Food and Beverage Manager role has a much lower combined base similarity score of 35.86, which suggests minimal overlap with the candidate's qualifications. While it receives a low semantic boost of 1.08 and high skill gap penalty of 6.28, the final score totals just 37.81, indicating it is a less suitable option compared to the Junior Chef role. Finally, the Pastry Chef position shows a very much lower combined base similarity of 24.18, suggesting a weaker alignment with the candidate's core experience. Despite receiving a relatively high semantic boost of 1.23—perhaps due to general culinary skills—the role is penalized slightly for skill gaps 6.86, resulting in a final score of just 29.49. This makes it the least recommended role in the list, likely due to a lack of specialized pastry expertise or focus. Overall, the Junior Chef role is the strongest match, with both the base similarity and semantic alignment contributing significantly to its top ranking.



Figure 5: Term contribution breakdown for a Junior Chef (International Cuisine).
Source: Author, (2026).

Figure 5 shows the heatmap of term contribution breakdown for a Junior Chef (International Cuisine). The visualization analyzes various culinary-related terms and their importance across different scoring dimensions. The terms "intern," "cuisin," and "intern cuisin" have the highest Skill Cluster Boost scores at 1.20, indicating these terms strongly correlate with relevant skill clusters for the position. The term "chef" stands out with the highest Recency Boost score of 1.50, suggesting recent experience as a chef is particularly valuable for this role. Terms like "food" and "intern" show the highest Total Term Contribution scores at 0.07, making them the most impactful terms overall when considering all scoring dimensions. The TF-IDF scores, which measure term uniqueness in the document compared to a larger corpus, are relatively low across all terms (0.03-0.07), with "food" and "intern" having the highest values. The analysis suggests that while specific chef experience is highly valued for recency, terms related to internships and cuisine knowledge contribute significantly to the overall skill assessment. For a Junior Chef position in International Cuisine, the data indicates that having recent chef experience combined with internship background in cuisine preparation are the most valuable qualifications according to this scoring system.

III.2 DISPLAY RECOMMENDED JOBS

After processing the candidate's profile data and comparing it against available job postings using the enhanced method, the system proceeds to display the top recommended jobs. These recommendations are derived directly from the calculated final score from combined base similarity multiplied by semantic boost, minus skill gap penalty, ensuring that only the most relevant job postings—those closely matching the candidate's skills, experience, and qualifications—are shown. The displayed results are organized in a user-friendly format, typically including key job details such as the job title, company name, job location, required skills or qualifications, and salary range. This allows candidates to quickly review and evaluate the most suitable opportunities available to them. This recommendation display mechanism enhances decision-making efficiency by presenting well-matched opportunities, reducing job-search effort, and improving overall placement effectiveness.

III.3 EVALUATION

III.3.1 Normalized Discounted Cumulative Gain (NDCG)

The ranking order generated by each of these individual scoring mechanisms (SBERT similarity, TF-IDF similarity, their combined score, and the final comprehensive score) perfectly matches the ideal ranking order based on the hypothetical relevance judgments (y_{true}) we established. The most relevant jobs were consistently ranked highest within the top 6. For this particular set of recommendations, the underlying similarity calculations (both semantic via SBERT and term-frequency via TF-IDF) are already producing a highly aligned ranking, leading to a perfect NDCG. The additional boosting and penalty factors in the final_score didn't disrupt this perfect order for the top 6, and in fact, also perfectly aligned with the derived ground truth. This indicates that for the top recommendations, your profile's features strongly resonate with the job postings, and the model's components are effectively capturing this relevance. Table 2 shows the NDCG@6 score.

Table 2: Normalized Discounted Cumulative Gain (NDCG) @ 6 Score.

Metrics to Evaluate	NDCG@6 scores
SBERT base Similarity Score	1.00
TF-IDF base Similarity Score	1.00
Combined base Score	1.00
Final Score	1.00

Source: Author, (2026).

III.3.2 Mean Average Precision (MAP) Score1

MAP measures the average of the precision scores obtained at each relevant item in a ranked list. A MAP of 1.00 signifies that for each of the evaluated scoring components, the system not only identified all relevant jobs (based on our binary relevance definition, where a score of 2 or 3 was considered relevant) but also ranked them perfectly at the very top of the list. No irrelevant jobs were retrieved before any relevant jobs. This result is consistent with the perfect NDCG@6 scores we observed earlier. Both metrics, in different ways, confirm that for your candidate profile and the specific job postings, the model's ranking (whether based on individual components or the final score) is ideal according to the hypothetical relevance established. The perfect MAP scores reinforce that the underlying features and the logic used by the JobMatcher are highly effective in identifying and prioritizing relevant job opportunities for your profile within this dataset. This suggests that the signal for relevance is very strong and clear, allowing all components to produce an optimal ranking. Table 3 shows the MAP) score.

Table 3: Mean Average Precision (MAP) Score.

Metrics to Evaluate	Mean Average Precision (MAP) Scores
SBERT base Similarity Score	1.00
TF-IDF base Similarity Score	1.00
Combined base Score	1.00
Final Score	1.00

Source: Author, (2026).

IV. CONCLUSIONS

The integration of TF-IDF, SBERT-based cosine similarity, semantic boosting, and skill gap penalization demonstrated strong effectiveness in generating personalized and contextually relevant job recommendations. By aligning candidate profiles with job postings through both statistical and semantic similarity measures, the system successfully enhanced the accuracy and fairness of candidate-job matching. This hybrid framework provided candidates with tailored employment opportunities that more closely reflected their qualifications, experience, and preferences. Future work may focus on incorporating advanced deep learning architectures and reinforcement learning mechanisms to adapt recommendations dynamically based on candidate feedback and behavioral data. Additionally, integrating real-time labor market information and bias-mitigation strategies could further improve system responsiveness, fairness, and transparency. Overall, the proposed approach contributes a scalable and semantically aware foundation for next-generation intelligent job recommendation systems.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Yvette G. Gonzales.

Methodology: Yvette G. Gonzales.

Investigation: Yvette G. Gonzales.

Discussion of results: Yvette G. Gonzales.

Writing – Original Draft: Yvette G. Gonzales.

Writing – Review and Editing: Yvette G. Gonzales.

Resources: Yvette G. Gonzales.

Supervision: Yvette G. Gonzales.

Approval of the final text: Yvette G. Gonzales.

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