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Development of Hanapbuh.AI: An AI-Powered Semantic Resume Matching System for Filipino Job Seekers

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ABSTRACT: The Philippine online job market is characterized by information overload and a heavy reliance on keyword-based search mechanisms that routinely fail to capture semantic skill alignment between candidates and available positions. This mismatch imposes substantial search costs on job seekers—particularly students and fresh graduates—and perpetuates a structural skills gap within the local labour market. This study aimed to design, develop, and evaluate HanapBuh.AI, a candidate-centric web application that automates resume parsing and performs semantic job matching to surface contextually relevant employment opportunities for Filipino job seekers.

Employing a descriptive-developmental research design, the study integrated spaCy (en_core_web_md) for named-entity recognition and the Sentence Transformer model (all-MiniLM-L6-v2) for 384-dimensional semantic embedding and cosine-similarity matching. The system was evaluated by n = 52 Filipino job seekers and fresh graduates using an instrument adapted from the ISO/IEC 25010 Software Quality Model across eight quality dimensions on a four-point Likert scale. Additional automated quality assurance was conducted via Apache JMeter, Google Lighthouse, and Playwright. The system achieved an overall General Weighted Average (GWA) of 3.76 out of 4.00 ("Strongly Agree"), with Usability (M = 3.80, SD = 0.45) as the highest-rated dimension, followed by Security (M = 3.77, SD = 0.49) and Portability (M = 3.77, SD = 0.48). Load testing confirmed a 0.00% error rate across 200 requests, and automated functional testing via Playwright recorded a 100% pass rate for all core user journeys. HanapBuh.AI effectively bridges the gap between candidate qualifications and publicly available job listings by replacing unguided keyword browsing with transparent, meaning-based matching. The system meets ISO/IEC 25010 quality thresholds and is technically validated for real-world deployment, constituting a viable proof-of-concept for semantic recruitment technology localized to the Philippine labor market.

KEYWORDS: semantic resume matching, natural language processing, job recommendation system, explainable AI, ISO/IEC 25010, Philippine labour market, SentenceTransformer, spaCy

1. INTRODUCTION

The rapid digitalisation of labour markets has produced an environment in which job seekers face a paradox of choice: an abundance of online postings, yet considerable difficulty identifying which roles genuinely align with their competencies and career trajectories (World Economic Forum, 2025). Contemporary job platforms predominantly employ keyword-based filtering mechanisms that match candidate profiles to vacancies through lexical overlap rather than contextual understanding. This approach systematically disadvantages applicants whose resumes describe skills using terminology that diverges from recruiter-defined keywords—a phenomenon compounded by the continuous evolution of occupational nomenclature and the projected 50% shift in core skill requirements forecast through 2030 (McKinsey & Company, 2025; PwC, 2025).

The Philippine labour market is particularly affected by this structural inefficiency. Despite sustained growth in the digital economy, a persistent skills gap impedes optimal matching between graduate competencies and employer requirements (World Bank, 2023). Filipino job seekers—especially students and fresh graduates—commonly report extended periods of unproductive "doomscrolling" through aggregated job portals, spending disproportionate cognitive effort on manually filtering listings that are irrelevant to their profiles (World Bank, 2025; SHRM, 2025). Existing platforms such as JobStreet, Indeed Philippines, and Kalibrr, while comprehensive in coverage, rely on keyword-centric ranking algorithms that do not adequately account for semantic equivalence between described skills and role requirements.

Advances in natural language processing (NLP), particularly transformer-based language models, now provide the technical capacity to address this limitation. Semantic embedding models—which represent text as high-dimensional vectors capturing contextual meaning—have demonstrated substantially superior matching precision compared to classical lexical methods such as TF-IDF in multiple empirical evaluations (Jirjees et al., 2025; Kurek et al., 2024; Ni, 2022). However, the practical deployment of such systems has predominantly focused on employer-centric applicant tracking systems (ATS), creating an "information asymmetry" whereby

hiring organisations receive algorithmic support while candidates continue to search with limited guidance (Kumar & Singh, 2024).

A secondary limitation of existing AI-driven recruitment tools is their "black box" character: recommendation scores are presented to users without qualitative justification, preventing candidates from understanding the basis for a match or identifying actionable steps to improve their market alignment (Waghmare et al., 2024; Hannibal & Bauer, 2025). Moreover, collaborative-filtering approaches that rely on user behavioural histories impose a "cold start" penalty on new users who have no interaction record on a platform (Rathelot et al., 2023). Taken together, these gaps reveal a clear need for a candidate-centric, content-based, transparent, and locally contextualised semantic matching system.

This study introduces HanapBuh.AI—a name derived from the Filipino word Hanapbuhay (livelihood), with the suffix replaced by "AI" to signify the system's technological core—as a direct response to the deficiencies identified above. Specifically, the system: (a) aggregates job postings from multiple Philippine-based platforms into a unified, searchable repository; (b) automatically parses uploaded resumes using a multi-stage NLP pipeline combining Pyresparser and spaCy; (c) generates semantic job recommendations via SentenceTransformer embeddings and cosine-similarity ranking; (d) provides transparent, plain-language justifications for each match; and (e) supplies skill-gap insights and course recommendations to support iterative professional development. The platform is designed exclusively for job seekers, explicitly excluding recruiter-side functionality, and is evaluated against the internationally recognised ISO/IEC 25010 Software Quality Model.

2. LITERATURE REVIEW

2.1 Theoretical Foundations

2.1.1 Information Retrieval Theory

Information Retrieval (IR) Theory, as formalised by Manning et al. (2008), concerns the principles by which systems store, index, and retrieve documents in response to user queries ranked by relevance. Within HanapBuh.AI, IR Theory governs the core technical pipeline: the user's resume functions as the query, and indexed job postings constitute the document corpus. The system evaluates relevance not through lexical frequency—as in classical TF-IDF approaches—but through semantic similarity computed over dense vector embeddings, ensuring that job listings are ranked according to contextual alignment with candidate competencies rather than arbitrary keyword overlap.

2.1.2 Career Development Theory

Super's (1957) Career Development Theory posits that vocational choices are an evolving expression of an individual's self-concept, shaped by personal strengths, aspirations, and developmental stage. HanapBuh.AI operationalises this theory at the interface and explanation layer of the system: by visualising extracted skills, providing match justifications, and recommending skill-development courses, the platform supports users in developing an accurate, nuanced understanding of their professional identity and its relationship to labour market opportunities. This approach acknowledges that job search is not a discrete event but a continuous process of self-positioning.

2.1.3 Technology Acceptance Model (TAM)

Davis's (1989) Technology Acceptance Model (TAM) attributes user adoption to two core perceptions: Perceived Usefulness (PU)—the degree to which a system enhances performance—and Perceived Ease of Use (PEOU)—the degree to which the system is considered effortless to operate. In this study, TAM structures the evaluation layer: technical quality characteristics such as Functional Suitability and Reliability operationalise PU, while Usability and Performance Efficiency operationalise PEOU. The ISO/IEC 25010 assessment instrument was designed to capture both constructs across eight quality dimensions, thereby linking software quality measurement to behavioural adoption intention.

2.2 Empirical Literature: From Keyword-Based to Semantic Matching

The evolution of automated resume screening reflects a broader transition in NLP from lexical to semantic representation. Early systems described by Kumar et al. (2021) and comparable approaches relied on TF-IDF vectorisation and bag-of-words models that demonstrated feasibility for automated candidate screening but exhibited well-documented limitations in capturing contextual skill equivalence. Patil et al. (2021) advanced this baseline through structured NLP pipelines for skill extraction, while Sujatha et al. (2021) demonstrated that selective feature engineering prior to model application significantly reduced noise in classification tasks.

The current state of the art is dominated by transformer-based architectures. Jirjees et al. (2025) reported that BERT combined with support vector machines achieved 94% classification accuracy in resume screening tasks, markedly outperforming classical lexical methods. Kurek et al. (2024) established the efficiency of zero-shot transfer learning using the all-MiniLM-L6-v2 model, which generates semantically rich 384-dimensional embeddings without task-specific fine-tuning. Bocharova and Malakhov (2024), in their

ResJobFit system, documented an 11-percentage-point improvement in ranking precision over classical baselines through domain-specific embedding strategies. More recently, Wang (2025) and Karthikeyan et al. (2025) have extended semantic matching to multi-dimensional candidate ability profiling and automated skill-gap remediation, respectively, while Frazzetto (2025) demonstrated that graph neural network architectures capture relational signals between candidates and positions that linear vector comparisons cannot represent.

2.3 Algorithmic Fairness, Transparency, and User Trust

As AI-mediated hiring becomes ubiquitous, researchers have increasingly scrutinised the ethical dimensions of automated decision-making. Soni (2024) and Delecraz et al. (2022) established that recruitment AI must be designed for both efficiency and equity, with the latter demonstrating that fairness

considerations must be embedded at the architectural level rather than applied post hoc. Ajjam et al. (2025) proposed scalable, fairness-aware neural matching frameworks validated at high-volume employment centres. Schmidt and Müller (2022) situate these developments within a broader transformation of global labour market intermediation by AI.

A consistent finding across recent studies is that matching accuracy alone is insufficient to secure user adoption: candidates must be able to understand and trust algorithmic recommendations. Hannibal and Bauer (2025) demonstrated through mixed-methods research that explanation quality—rather than explanation presence alone—determines the degree to which AI recommendations influence user confidence. Kumar and Singh (2024) showed that visual analytics dashboards that surface the reasoning behind match scores substantially improve interpretability. Olanrewaju et al. (2023) confirmed that personalised, explanation-enriched AI assistants increase engagement and perceived utility in employment support contexts. Bajaj and Shivani (2025) additionally proposed blockchain-based credential verification as a complementary mechanism for enhancing trust within digital recruitment ecosystems.

2.4 Regional Adaptation and Localised Labour Market Systems

The effectiveness of job-matching AI is demonstrably context-dependent. Sangwa et al. (2025) reported that an NLP-based labour market simulation localised to Rwanda reduced projected graduate unemployment by 15%, underscoring the primacy of regional specificity in system design. Al-Khalifah et al. (2025) and Rathelot et al. (2023) similarly documented the importance of adapting systems to the high-volume, platform-specific dynamics of the Saudi and Swedish labour markets, respectively. Alonso Sun (2025) demonstrated that domain-specific fine-tuning via low-rank adaptation (LoRA) substantially improves LLM-based matching precision in specialised industry sectors such as hospitality.

In the Philippine context, the skills gap between graduate competencies and employer expectations constitutes a structural barrier to efficient labour market matching (World Bank, 2023). Farell et al. (2024) identified persistent misalignment between vocational graduate profiles and employer expectations that content-based filtering approaches can ameliorate. Wiles and Horton (2025) cautioned, however, that indiscriminate adoption of generative AI in job search support—without attention to specificity and signal quality—risks degrading the informational value of candidate-employer interactions. These considerations collectively justify HanapBuh.AI's emphasis on localised job source integration, candidate-centric transparency, and explainable semantic matching.

2.5 Research Gaps Addressed by This Study

The foregoing review identifies four principal gaps that HanapBuh.AI is designed to address. First, the dominant employer-centric orientation of existing AI recruitment systems leaves candidates without actionable guidance: the system inverts this dynamic by providing a candidate-only, explanation-enriched matching interface. Second, the pervasive "black box" problem is resolved through an explainable AI component that generates qualitative, plain-language justifications alongside quantitative match percentages. Third, the cold-start limitation of collaborative-filtering systems is avoided through exclusive reliance on content-based semantic matching, which produces high-quality recommendations immediately upon a user's first resume upload. Fourth, and most distinctively, HanapBuh.AI localises the AI pipeline to the Philippine labour market by integrating domestic job sources and acknowledging the linguistic and occupational characteristics of Filipino professional profiles.

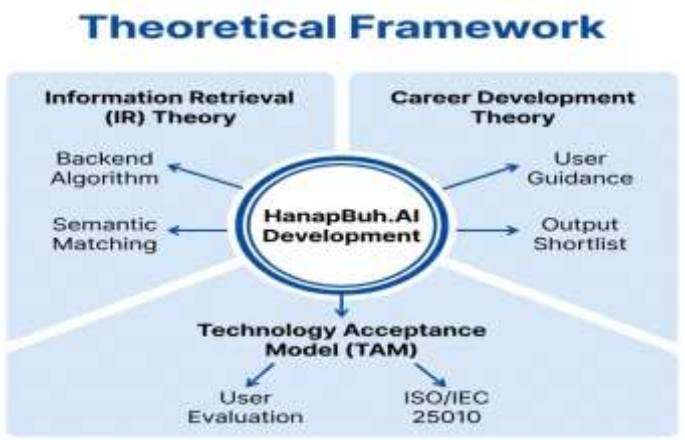

Fig.1. ***Theoretical Framework***

Figure 1 illustrates the theoretical foundation of HanapBuh.AI, showcasing the interplay between three core academic pillars that guide the system's development. Information Retrieval (IR) Theory serves as the technical backbone, governing the backend algorithms and semantic matching logic to ensure that job recommendations are grounded in measurable relevance. Career Development Theory anchors the user-facing experience, focusing on providing meaningful guidance and a transparent output shortlist to support informed career decision-making. Finally, the Technology Acceptance Model (TAM) provides the framework for evaluating the system's success, linking user perceptions of usefulness and ease-of-use to formal software quality standards like ISO/IEC 25010. Together, these theories ensure that the development of HanapBuh.AI remains both technically precise and human-centric.

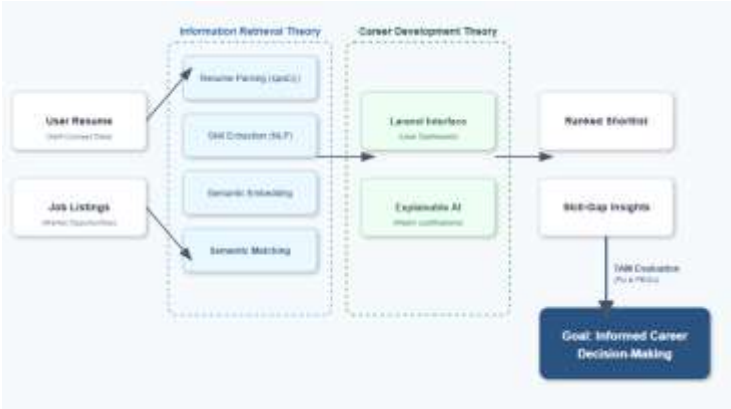

Fig. 2. ***Conceptual Framework***

The conceptual framework of HanapBuh.AI, as illustrated in Figure 2, demonstrates a theoretically-grounded pipeline that transforms raw input data into actionable career goals. The process begins with the Inputs - the User Resume (Self-Concept Data) and Job Listings (Market Opportunities) - which are fed into the Information Retrieval Theory layer. This layer serves as the technical core of the system, involving resume parsing via spaCy, skill extraction through NLP, and semantic embedding to facilitate intelligent semantic matching. The analyzed data then transitions into the Career Development Theory layer, which governs the user-facing Laravel Interface and the Explainable AI transparency layer to provide meaningful match justifications. This analysis results in two primary Outputs: a Ranked Shortlist of job matches and actionable Skill-Gap Insights. Finally, the framework incorporates a TAM Evaluation based on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) to ensure the system effectively achieves the ultimate Goal of fostering informed career decision-making for Filipino job seekers.

3. METHODOLOGY

3.1 Research Design

This study employed a descriptive-developmental research design. The descriptive component captured Filipino job seekers' current experiences with keyword-based job portals, their perceived pain points, and their evaluation of the developed system's performance against ISO/IEC 25010 quality criteria. The developmental component encompassed the iterative design, implementation, and refinement of the HanapBuh.AI prototype, with each iteration guided by empirical feedback collected through structured user evaluation sessions. The two components are mutually reinforcing: descriptive findings from user evaluations identified specific limitations that informed subsequent developmental improvements, while each developmental iteration became the subject of further descriptive assessment.

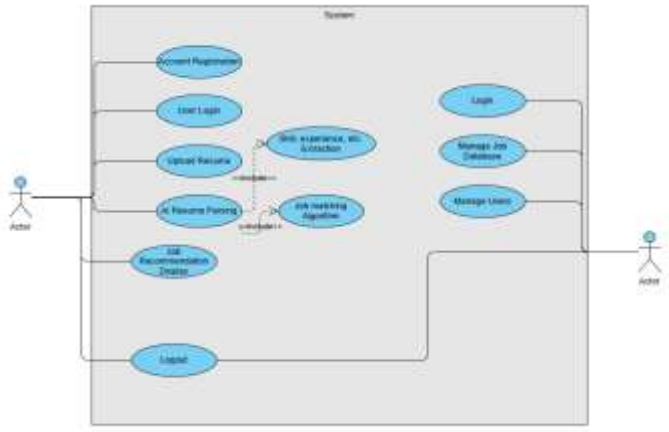

Fig. 3. ***Use Cases***

3.2 Research Locale and Deployment Context

Testing and evaluation were conducted at Centro Escolar University (CEU), Manila. The HanapBuh.AI system was deployed on a cloud-hosted Virtual Private Server (VPS) using a containerised architecture (Docker) to ensure environmental consistency and 24/7 availability throughout the evaluation period (April 2026). Participants accessed the system remotely via a publicly available URL secured with SSL/TLS encryption, allowing platform-independent access through standard desktop and mobile web browsers without additional software installation.

3.3 Participants

The study recruited n = 52 respondents comprising job seekers and fresh graduates from a target batch of CEU students. Required sample size was determined a priori using Yamane's Formula ($n = N / [1 + Ne^2]$) with a population of N = 57 and a 5% margin of error, yielding a minimum sample of $n_0 = 50$. The achieved sample of 52 represents a 91.2% response rate, satisfying and slightly exceeding this threshold. Participants were selected via convenience sampling, as this approach is pragmatically appropriate for developmental system evaluation and ensures that respondents represent the actual target demographic of the platform. Inclusion criteria required participants to be current students or recent graduates who were actively seeking employment or contemplating the job market. Individuals under 18 years of age, current HR or recruitment professionals, and participants without stable internet access were excluded.

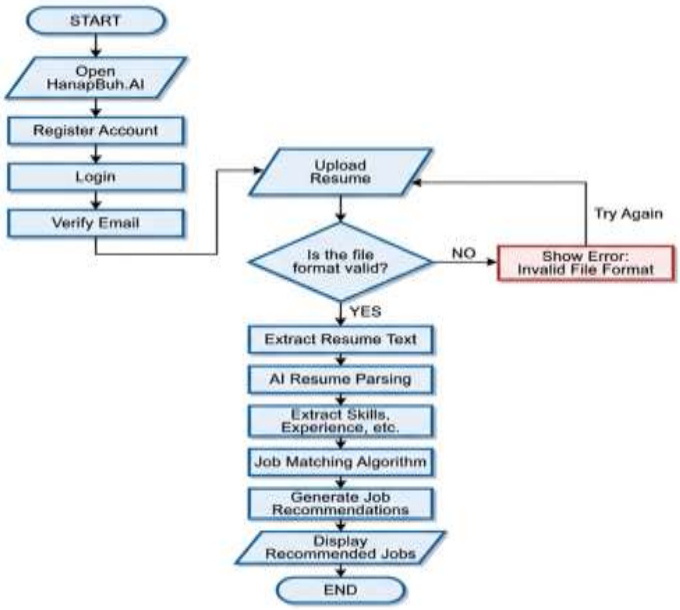

Fig. 4. ***Flowchart***

3.4 System Architecture and AI Pipeline

The HanapBuh.AI system is built on the Laravel (PHP) web framework, providing MVC architecture, secure user authentication with OTP email verification, and a responsive user interface styled with Tailwind CSS. Python functions are integrated into the backend to execute the AI processing pipeline. The data layer is populated through a combination of official APIs (where available, e.g., JobStreet) and custom Python web scrapers that strictly adhere to the Robots Exclusion Protocol (robots.txt) and implement a 3-second rate limit between requests. During the April 2026 evaluation period,

approximately 1,200 active job postings were aggregated from OnlineJobs.ph, Indeed Philippines, Kalibrr, JobStreet and JobsDB, Bossjob and WorkAbroad.ph, and LinkedIn.

Upon a user's resume upload, the pipeline executes the following stages in sequence: (1) raw text extraction and PDF structural validation via Pyresparser; (2) named-entity recognition and professional entity classification (skills, job titles, educational qualifications, certifications) using spaCy's en_core_web_md model, which provides 680,000 word vectors for entity recognition; (3) semantic embedding of the extracted candidate profile and all indexed job descriptions using the SentenceTransformer all-MiniLM-L6-v2 model, producing 384-dimensional dense vectors for each text unit; (4) cosine-similarity computation between the candidate embedding and each job-description embedding to generate a ranked relevance score; and (5) generation of plain-language match justifications and skill-gap recommendations surfaced through the Laravel interface's explainable AI transparency layer.

3.5 Algorithms

1. SEMANTIC MATCHING ALGORITHM

```
# Location: App/flask_api_new.py -&gt; get_best_role()
# Uses Sentence-Transformers to compare Profile vs Roles
def get_best_role(resume_skills, parsed_data):
# Load the transformer model (all-MiniLM-L6-v2)
resume_embedding = model.encode(resume_context, convert_to_tensor=True)
# Calculate Cosine Similarity against all roles in the dataset
role_similarities = []
for role_description in job_roles:
role_embedding = model.encode(role_description, convert_to_tensor=True)
similarity = util.pytorch_cos_sim(resume_embedding, role_embedding).item()
```

2. DEGREE PRIORITY BOOST:

```
# If degree matches field, add +0.40 to ensure education priority
if target_boost_field == current_role_field:
similarity += 0.40
role_similarities.append((role_description, similarity))
# Sort by highest similarity
role_similarities.sort(key=lambda x: x[1], reverse=True)
return role_similarities[0]
```

3. NLP EXTRACTION & REFINEMENT

```
# Location: App/flask_api_new.py -&gt; _refine_name() &amp;amp; detect_degree_from_text()
# Custom logic to clean up AI extraction for Philippine resumes
def _refine_name(parsed_data, resume_plain_text):
# Strategy 1: Derive from LinkedIn URL
# Strategy 2: Derive from Email pattern (e.g. john.doe@email.com)
# Strategy 3: Top-of-page layout analysis
# Strategy 4: Parser result validation
def detect_degree_from_text(text):
# Abbreviation mapping for PH degrees
ABBR_MAP = {
&quot;bscs&quot;: &quot;BS Computer Science&quot;,
&quot;bsit&quot;: &quot;BS Information Technology&quot;,
&quot;bsa&quot;: &quot;BS Accountancy&quot;,
&quot;bsce&quot;: &quot;BS Civil Engineering&quot;,
}
# Pattern matching for &quot;Bachelor of Science in...&quot;
for pat in DEGREE_PATTERNS:
m = re.search(pat, text.lower())
if m: return m.group(0).title()
```

4. BATCH JOB MATCHING

```
# Location: App/flask_api_new.py -&gt; batch_match_jobs()
# Matches one profile against multiple scraped jobs simultaneously
@app.route(&#39;/batch_match&#39;,
methods=[&#39;POST&#39;])
def batch_match_jobs():
# 1. Encode Resume into a vector
resume_embedding = model.encode(resume_context, convert_to_tensor=True)
# 2. Encode all Jobs in a single matrix (very fast)
job_embeddings = model.encode(job_contexts, convert_to_tensor=True)
# 3. Compute Cosine Similarity matrix
similarities = util.cos_sim(resume_embedding, job_embeddings)[0].tolist()
# 4. Apply &quot;Recommended Field&quot; bonus (+15% if strings match)
if recommended_field.lower() in job_text:
match_score = min(100, match_score + 15)
```

3.6 Instrumentation

The primary evaluation instrument was a 40-item structured questionnaire adapted from the ISO/IEC 25010 Software Quality Model, employing a four-point Likert scale (4 = Strongly Agree; 3 = Agree; 2 = Disagree; 1 = Strongly Disagree). The instrument comprised five items per quality dimension across eight dimensions: Functional Suitability, Performance Efficiency, Compatibility, Usability, Reliability, Security, Maintainability, and Portability. Content and face validity were established through expert review by the study's research supervisor. Instrument reliability and item clarity were assessed through a pilot test with five participants who met inclusion criteria but were excluded from the main sample. Pilot feedback informed minor wording adjustments prior to final administration.

3.7 Data Gathering Procedure

Data collection proceeded in three phases during April and May 2026. In the Preparation Phase, the research instruments and data collection protocols were reviewed and approved by the institutional Research Professor. In the System Use Phase, participants registered for a HanapBuh.AI account, underwent OTP email verification, uploaded a resume in PDF or DOCX format, and explored the system's job recommendations and AI analysis output for a minimum of 15 minutes. In the Survey Administration Phase, participants completed the 40-item ISO/IEC 25010 questionnaire via an online form immediately

following their system interaction session. Responses and system usage logs were compiled in tabular form for statistical analysis.

3.8 Statistical Analysis

Descriptive statistics were used throughout. Yamane's Formula determined minimum sample size. Frequency and percentage distributions characterised respondent demographics. Weighted means (WM) were computed for each Likert-scale item and aggregated by quality dimension, with standard deviations (SD) quantifying response consistency. The General Weighted Average (GWA = ΣWM / k, where k = 8 dimensions) represented overall system quality. Interpretive thresholds followed the scale: 3.26–4.00 = Strongly Agree (Excellent); 2.51–3.25 = Agree (Good); 1.76–2.50 = Disagree (Fair); 1.00–1.75 = Strongly Disagree (Poor). Automated technical performance was assessed through Apache JMeter load testing (50 concurrent users, 200 total samples), Google Lighthouse auditing, and Playwright end-to-end functional testing.

3.9 Ethical Considerations

All participants provided informed consent prior to participation and were advised that engagement was voluntary and could be discontinued at any time without penalty. Confidentiality was maintained by removing personal identifiers from all uploaded resumes prior to analysis; resume files were stored on the secured VPS and deleted upon study completion. All data were used exclusively for academic purposes. The study excluded individuals under 18 years of age from participation. Ethical web scraping practices were strictly observed, including compliance with each source platform's robots.txt file and implementation of request rate limits to avoid service disruption.

4. RESULTS

4.1 Identified Gaps in Existing Systems (Research Question 1)

A systematic review of the related literature identified five principal gaps in existing AI-driven job-matching systems. These are summarised in Table 1 alongside the specific mechanism through which HanapBuh.AI addresses each gap.

Table 1 : **Identified Gaps in Automated Resume-to-Job Matching and System Responses**

Author / Year	Study	Identified Gap	HanapBuh.AI Response
Waghmare et al. (2024)	AI-Based Resume Matching and Prediction	Lack of explainable output; systems provide quantitative match scores without qualitative reasoning.	Explainable AI component generates plain-language justifications and percentage scores for each match.
Akhtar et al. (2025)	AI-Driven Intelligent Resume Recommendation Engine	Lack of robustness for unstructured PDF layouts; high error rates on non-standard documents.	Specialised PDF-only parsing pipeline via Pyresparser maintains structural integrity across diverse resume formats.
Sangwa et al. (2025)	AI-Driven Job Matching Study	Over-reliance on simulated data; theoretical models underperform on real-world, unstructured input.	System evaluated on actual candidate resumes from the local labour market rather than idealised datasets.
Rathelot et al. (2023)	How Can AI Improve Search and Matching?	Collaborative filtering creates a cold-start problem for new users lacking behavioural history.	Content-based semantic matching operates entirely on resume text, providing strong results from the first upload.
Kumar & Singh (2024)	Intelligent Resume–Job Matching Framework	Recruiter-centric visual analytics provide HR insight but leave candidates without guidance.	System is candidate-only; all match analytics and skill-gap insights are surfaced exclusively to the job seeker.

The identified gaps collectively confirm that the dominant design tradition in AI recruitment prioritises employer efficiency over candidate empowerment, and quantitative scoring over interpretable guidance. These findings directly informed HanapBuh.AI's architectural decisions.

4.2 Implemented Technologies (Research Question 2)

The technology stack underpinning HanapBuh.AI is detailed in Tables 2a and 2b, distinguishing between the core software development environment and the AI processing components.

Table 2a :**Core Software Development Stack**

Technology	Implementation	Technical Specifications
spaCy (en_core_web_md)	Resume Parsing & NER	Medium-sized English model with 680,000 word vectors for entity recognition.
SentenceTransformer (all-MiniLM-L6-v2)	Semantic Matching	Generates 384-dimensional dense embeddings; cosine-similarity ranking against job descriptions.
Pyresparser / PDF Analysis	Text Extraction	Specialised pipeline for unstructured, multi-column PDF resume layouts.
Python Web Scrapers	Data Aggregation	Custom scrapers respecting robots.txt; 3-second rate limiting. ~1,200 postings aggregated (April 2026).

Table 2b :**AI and Data Processing Technologies**

Software / Tool	Category	Core Function
Python, HTML, CSS	Programming Languages	Backend AI logic and responsive frontend markup.
Laravel Framework	Web Framework	MVC architecture, secure authentication, user dashboard.
Tailwind CSS	CSS Framework	Modern, responsive UI styling and layout.
Visual Studio Code	IDE	Primary development and debugging environment.
Git / GitHub	Version Control	Source code management and version tracking.
Docker / Cloud VPS	Deployment	Containerised deployment for environment consistency and 24/7 availability.

The selection of all-MiniLM-L6-v2 is directly supported by Kurek et al.'s (2024) empirical validation of this model's efficiency in zero-shot matching tasks, while the choice of spaCy's medium English model balances computational performance with named-entity recognition accuracy appropriate for professional documents.

4.3 Software Quality Evaluation (Research Question 4)

Table 3 ISO/IEC 25010 Software Quality Evaluation Results (n = 52)

Quality Dimension	M	SD	Verbal Interpretation
Functional Suitability	3.74	0.48	Strongly Agree
Performance Efficiency	3.71	0.51	Strongly Agree
Compatibility	3.73	0.54	Strongly Agree
Usability	3.80	0.45	Strongly Agree
Reliability	3.71	0.52	Strongly Agree
Security	3.77	0.49	Strongly Agree
Maintainability	3.75	0.50	Strongly Agree
Portability	3.77	0.48	Strongly Agree
Overall GWA	**3.76**	**0.50**	Strongly Agree

Note. *Four-point Likert scale: 3.26–4.00 = Strongly Agree (Excellent); 2.51–3.25 = Agree (Good). M = Weighted Mean; SD = StandardDeviation.*

4.4 Automated Technical Performance (Research Question 5)

The system was subjected to three independent automated quality assurance evaluations. Results are reported in Tables 4, 5, and 6.

Table 4 : Apache JMeter Load Testing Results (50 Concurrent Users, n = 200 Requests)

Step	Samples	M (ms)	Min (ms)	Max (ms)	Error %	Throughput
Step 1: Get CSRF Token	50	2,251	251	4,287	0.00%	3.6/sec
Step 2: User Login	50	6,258	768	9,445	0.00%	2.4/sec
Step 3: Get API Endpoint	50	2,806	792	5,331	0.00%	2.4/sec
Step 4: Semantic Job Search	50	2,245	926	4,883	0.00%	2.3/sec
TOTAL	200	3,390	251	9,445	0.00%	8.6/sec

Note. *Testing performed on a local server environment with simulated network latency. M = average response time in milliseconds.*

Table 5: Google Lighthouse Performance Metrics Across Key Application Pages

Metric	Landing Page	Home / Job Recs.	Jobs / Resume Page
Performance Score	98	74	74
Accessibility Score	90	90	92
Best Practices Score	81	81	81
SEO Score	100	92	92
First Contentful Paint	0.6 s	2.3 s	2.1 s
Largest Contentful Paint	1.1 s	2.4 s	2.2 s
Speed Index	0.6 s	2.3 s	2.9 s

Note. *Scores range from 0 to 100; 90–100 = excellent; 50–89 = moderate; 0–49 = poor (Google Lighthouse classification).*

Table 6: Playwright Automated Functional Testing Results

Test Step	Status	Observation
1. Account Registration	PASSED	Successful database entry confirmed.
2. OTP Email Verification	PASSED	Token generation and email delivery verified.
3. Secure Login	PASSED	Dashboard redirection confirmed post-authentication.
4. AI Data Injection	PASSED	Mock AI analysis pipeline execution verified.
5. Semantic Job Search	PASSED	Semantic search results retrieved and validated.
Overall Result (43.4 s)	PASSED	100% pass rate across all core user journey steps.

5. DISCUSSION

5.1 User Evaluation and Quality Characteristics

The overall GWA of 3.76 (SD = 0.50) indicates that the 52 respondents collectively and strongly affirmed HanapBuh.AI's quality across all eight ISO/IEC 25010 dimensions. The consistently low standard deviations (ranging from 0.45 to 0.54) reflect a high degree of inter-rater consensus, lending confidence to the robustness of these findings despite the relatively modest sample size. Usability emerged as the highest-rated dimension (M = 3.80, SD = 0.45), consistent with the design priority placed on transparent, plain-language match explanations and an intuitive Laravel-driven interface. This finding aligns with Kumar and Singh (2024), who demonstrated that explanation-enriched interfaces substantially improve user comprehension of AI recommendations, and with Hannibal and Bauer (2025), who linked explanation quality—rather than mere presence—to user trust. The high Usability rating suggests that the explainable AI component successfully addresses the transparency gap identified in the related literature.

Security (M = 3.77, SD = 0.49) and Portability (M = 3.77, SD = 0.48) ranked jointly second. The strong security rating reflects user confidence in the system's OTP-based authentication, SSL/TLS data transmission, and institutional data handling commitments—particularly salient given that users were uploading personally identifiable resume documents. Portability scores confirm that the responsive, platform-independent web

application design was successfully perceived as accessible across devices, consistent with the system's deliberate adoption of Tailwind CSS for adaptive layout.

Performance Efficiency (M = 3.71, SD = 0.51) and Reliability (M = 3.71, SD = 0.52) recorded the lowest scores within the "Strongly Agree" band. These results are interpretively coherent: transformer-based NLP inference via SentenceTransformer introduces inherent computational latency—particularly for large or complex PDF documents—that is not present in classical keyword-matching systems. Additionally, the real-time retrieval of job postings from external sources introduces network-dependent variability. These findings echo Akhtar et al.'s (2025) observation that transformer-based systems exhibit performance trade-offs when processing real-world, unstructured inputs. Notably, even the lowest-rated dimensions considerably exceeded the "Agree" threshold boundary (2.51), indicating that latency was perceived as acceptable rather than problematic.

5.2 Technical Performance

The JMeter load test results (Table 4) provide objective validation of the system's stability under concurrent user demand. A 0.00% error rate across 200 simulated requests confirms that the containerised deployment architecture maintained response integrity without failures or timeouts at the tested concurrency level. The Login step's comparatively elevated average latency (M = 6,258 ms) reflects the computational overhead of bcrypt password hashing combined with OTP verification—a security-performance trade-off that is standard in production web applications and was acceptable to respondents as evidenced by the Security dimension rating.

Google Lighthouse results (Table 5) reveal a meaningful performance distinction between the static landing page (score: 98, FCP: 0.6 s) and the dynamic job recommendation pages (score: 74, FCP: 2.1–2.3 s). This divergence is architecturally expected: the landing page serves pre-rendered static content, whereas the home and jobs pages execute real-time NLP inference and database queries to assemble personalised recommendation lists. The consistency of total blocking time at 0 ms across all pages indicates that the JavaScript execution model does not impede rendering responsiveness. Accessibility scores consistently met or exceeded the 90-threshold across all pages, ensuring compliance with inclusive design principles—a dimension underscored by Kuznetsov et al.'s (2025) work on accessible employment systems.

Playwright's automated functional test suite (Table 6) recorded a 100% pass rate across all five core user journey steps in 43.4 seconds, confirming that the full pipeline—from account registration through OTP verification, secure login, AI resume analysis, and semantic job retrieval—executes without runtime errors. This result provides empirical validation that the system is technically ready for real-world deployment at the current scale.

5.3 Addressing Identified Research Gaps

The results collectively demonstrate that HanapBuh.AI systematically addresses each gap identified in the related literature (Table 1). The explainable AI component directly resolves the black-box limitation documented by Waghmare et al. (2024), providing both percentage match scores and qualitative skill-alignment narratives for every recommendation. The Pyresparser-based PDF parsing pipeline mitigates the unstructured-document robustness limitations identified by Akhtar et al. (2025). The system's exclusive reliance on content-based semantic matching eliminates the cold-start penalty associated with collaborative-filtering approaches, as described by Rathelot et al. (2023), enabling high-quality recommendations for first-time users with no prior platform interaction. The platform's candidate-only design philosophy inverts the recruiter-centric orientation critiqued by Kumar and Singh (2024). Finally, the empirical deployment on actual Filipino job seeker resumes—rather than simulated datasets—directly addresses the ecological validity concern raised by Sangwa et al. (2025).

5.4 Positioning Within the Literature

HanapBuh.AI occupies a distinctive position within the AI recruitment literature as the first publicly evaluated, candidate-centric, explainable semantic matching system localised to the Philippine labour market. Its transformer-based architecture is consistent with the trajectory established by Jirjees et al. (2025), Kurek et al. (2024), and Bocharova and Malakhov (2024), while its explicit commitment to transparency and candidate empowerment extends the fairness-and-trust agenda articulated by Soni (2024), Delecraz et al. (2022), and Hannibal and Bauer (2025). The strong evaluation scores suggest that the TAM constructs of Perceived Usefulness and Perceived Ease of Use were successfully realised in the deployed system, indicating meaningful adoption potential within the target population.

5.5 Limitations

Several limitations warrant acknowledgement. First, the sample (n = 52) was recruited through convenience sampling from a single institution (CEU, Manila) and may not be representative of the broader Filipino job-seeking population across demographic groups, geographic regions, or experience levels. Second, the evaluation period was confined to April–May 2026, and the job posting database (~1,200 postings) reflects the availability of specific sources at that time; link expiry and API access changes may affect replicability. Third, the study does not measure employment outcomes: whether HanapBuh.AI improves actual job placement rates relative to conventional platforms remains an open empirical question. Fourth, the AI models employed are pre-trained on general English corpora and may not optimally handle highly specialised professional terminology or Taglish (Tagalog-English code-switching) linguistic patterns prevalent in Philippine labour market communications. Fifth, the Lighthouse performance scores on

dynamic pages (74) suggest room for optimisation, particularly for users with slower mobile connections.

6. CONCLUSION

This study presented HanapBuh.AI, an AI-powered semantic resume matching system designed to address the structural inefficiencies of keyword-based job search in the Philippine digital labour market. By integrating spaCy-based named-entity recognition with SentenceTransformer semantic embeddings and a transparent explainable AI layer, the system provides Filipino job seekers with a candidate-centric, meaning-based alternative to conventional job portals.

The system achieved an overall GWA of 3.76 ("Strongly Agree") across all eight ISO/IEC 25010 quality dimensions, with Usability emerging as the top-rated characteristic—validating the system's design commitment to transparent, interpretable recommendations. Automated quality assurance testing confirmed a 0.00% error rate under concurrent load and a 100% pass rate across all automated functional test scenarios, establishing the system's technical readiness for production deployment.

These findings constitute a proof-of-concept that a candidate-centric, explainable, content-based semantic matching architecture is both technically viable and highly valued by target users. The study addresses five documented gaps in existing AI recruitment systems—opacity, cold-start limitations, recruiter-centric design, unstructured-document fragility, and lack of regional localisation—and provides an empirically validated framework for future development of transparent, equitable, and locally contextualised employment AI.

Future research should pursue: (1) fine-tuning of the NLP pipeline on Taglish and domain-specific Philippine occupational language corpora; (2) integration of OCR capabilities to extend parsing to scanned or image-based resumes; (3) development of a predictive skill-gap roadmap that moves beyond explaining current match quality to prescribing specific upskilling pathways; (4) longitudinal controlled evaluation comparing employment outcomes between HanapBuh.AI users and those using traditional keyword-filtering platforms; and (5) model distillation or edge-computing deployment to reduce transformer inference latency on dynamic application pages.

Link to Software Presentation:

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