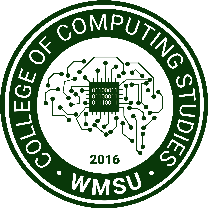
****Republic of the Philippines Western Mindanao State University **College of Computing Studies**

DEPARTMENT OF COMPUTER SCIENCE

Zamboanga City

## RxVision: OCR-based Medical Prescription Reader Using TrOCR and BioBERT

A Thesis Presented to the Faculty of Department of Computer Science College of Computing Studies

In Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science

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## Abstract

Handwritten medical prescriptions continues to be widely used across the Philippines, particularly in regions with limited access to digital health technologies. However, such prescriptions often pose challenges related to legibility, accuracy, and verification, leading to potential medication errors, misinterpretation, and prescription fraud. This aims to address these issues by developing RxVision, an AI-driven system that combines TrOCR (Transformer-based Optical Character Recognition) for text extraction from handwritten prescriptions and BioBERT, a domain-specific NPL model, for contextual verification of medical prescription data. RxVision is designed for both healthcare professionals and the general public, enabling users to scan and validate prescriptions via a mobile application. It includes a verification feature that checks prescription authenticity and ensures that prescriptions older than six months are flagged as expired, prompting user to consult their physician for a new one. The system will be developed by using publicly available datasets, including the IAM Handwriting Database, MIMIC-III, and RxNorm to train and evaluate its performance. This research focuses on developing a functional prototype that improves prescription readability, reduces the risk of misinterpretion, and enhance patient safety. Its initial implementation in Zamboanga City serves as a foundation for nationwide deployment in the future.

### Keywords:

* BioBERT, OCR, Prescription Verification, TrOCR, NLP.

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# CHAPTER I INTRODUCTION

### Background of the Study

Healthcare providers still frequently provide patients their drug instructions by handwriting prescriptions. However, their validity and legibility frequently provide significant obstacles for both the public and pharmacists, which can result in potential fraud and drug errors. Misunderstanding medical prescriptions can lead to inaccurate dosages or even the wrong medication being administered, putting patient safety at risk. Many medical professionals and patients continue to write prescriptions by hand despite the developments in digital healthcare technologies, especially in Zamboanga City, Philippines, where digital adoption is still relatively low.

In able to deal with this issue, we will be developing RxVision an AI-powered OCR-based medical prescription reader and verifier that will not only be used to extract text from handwritten prescriptions but will also verifies the legitimacy of the prescription. By using TrOCR for the Optical Character Recognition (OCR) and BioBERT for the Natural Language Processing (NLP) verification, RxVision guarantees that the prescription are both accurately transcribed and checked at variance with the official databases. This system will be accessible to the public such as, patients and caregivers as well as the pharmacist, physicians, and other healthcare professionals, enabling them to check the prescriptions before purchasing or administering medications. Additionally, to prevent the use of past due prescriptions, RxVision will not generate results for prescriptions older than six months, advising patients to consult their physicians for a new prescription.

Although this study is currently focused on the Philippines, the challenges that it resolves are in a global situation. In other countries, with emerging economies, still relies on a handwritten prescription as a standard practice. These regions faces similar issues of legibility, lack of verification, and prescription fraud. Therefore, the solution proposed in this study, RxVision, holds potential value for adoption in the international healthcare system that are facing similar challenges.

### Statement of the Problem

Handwritten medical prescriptions pose a significant problems in the healthcare industry due to the reason that they are difficult to read, which constantly results in medication errors and misinterpretation. This study emphasizes the problems in reading and verifying handwritten medical prescriptions, which leads to medication errors, fraudulent prescriptions, and improper administration. This research aims to develop an AI- driven system capable of both accurate tasting recognition and prescription verification to ensure the patients safety and prevent misuse.

### Objectives

The general objective of this study is to develop the RxVision, an AI-driven OCR-based medical prescription reader and verifier that correctly recognizes, interpret, and validates handwritten prescriptions to limit the errors, detect deceptive prescriptions, and enhance the prescription readability for both healthcare professionals and general public use.

* To identify and analyze the common problems encountered in dealing with handwritten prescriptions.
* To develop and deploy an OCR-based system using TrOCR for extracting text from handwritten prescriptions.
* To integrate and implement BioBERT, and NLP techniques to verify, correct, and interpret collected data.
* To create and test prototype system that correctly reads and verifies prescriptions, ensuring accuracy and lessen misinterpretation.
* To analyze the system’s performance based on accuracy and usability through user testing testing with the healthcare professionals and general reads.

### Scope and Limitations

**Scope :**

RxVision is an AI-powered OCR and verification system developed to read and translate handwritten medical prescription into a readable text. The system will be developed in Zamboanga City, Philippines and will be available for both healthcare professional and general public. The system will allow patients, caregivers, including healthcare professionals to scan prescription via mobile application to ensure readability and validity before purchasing or administering medication. The system also integrates fraud detection, securing that the prescription comes from a licensed medical professional.

### Limitations:

1. RxVision will not process prescriptions older than six months, advising patients to request a new prescription from their physician.
2. While RxVision extracts and verifies prescription, final interpretation and medical advice still requires professional validation from a licensed medical professional.
3. The system supports English-language medical prescription, with potential multi lingual support in the future.

In order to access the issue of illegible medical prescriptions. RxVision aims to create an Ai-powered solution that enhances prescription accuracy, improves patient safety, and streamline healthcare work flow.

### Significance of the Study

### 

### This Stakeholders are expected to benefit in the development of RxVision :

* + **Patients and Regular User:** RxVision will provide a simple way to interpret prescription to reduces confusion and ensuring proper medication adherence.
  + **Pharmacists and Healthcare Providers:** The System will reduce the time spent in manually interpreting the hand written prescription , minimizing the misinterpretation and administer the medication safety.
  + **Hospitals and Clinics:** Healthcare institution will also benefit from increasing efficiency in prescription process , reducing burdens and improve patient service.
  + **Healthcare Technology Researchers and Developers:** This study provides a foundation for future researchers.
  + **Government Health Agencies and Policymakers:** Government sectors can gain leverage the outcome to improve the prescription handling protocols and enhances patient safety.

### Definition of Terms

*Table 1: Definition of Terms*

|  |  |
| --- | --- |
| **Term** | **Definition** |
| 1. Optical Character Recognition (OCR) | A technology that converts images of handwritten or printed text into machine-relatable digital text.  RxVision uses OCR to extract text from handwritten medical prescription.  (Source: Ray Smith, "An Overview of the Tesseract OCR Engine," *Proceedings of Document Analysis and Recognition*, 2007) |
| 2. TrOCR  (Transformer- based OCR) | A deep learning model developed by Microsoft that utilizes transformers to recognize and extract text from handwritten documents with high accuracy.  (Source: Li et al., "TrOCR: Transformer-based Optical Character Recognition with Pre-trained Models," *arXiv preprint arXiv:2109.10282*, 2021) |
| 3. Natural Language Processing (NLP) | A field of artificial intelligence (AI) that allows computers to analyze , interpret and understand human language.  In this study NPL is used to verify the accuracy and legitimacy of prescription details.  (Source: Jurafsky & Martin, *Speech and Language Processing*, 2021) |
| 4. BioBERT  (Biomedical BERT) | A specialized NLP model trained on biomedical text, designed to improve understanding of medical terminologies. RxVision integrates BioBERT for validating prescription information.  (Source: Lee et al., "BioBERT: A Pre-trained Biomedical Language Representation Model for Biomedical Text Mining," *Bioinformatics*, 2020) |

|  |  |
| --- | --- |
| **Term** | **Definition** |
| 5. Prescription Verification | It is the process that confirms whether the prescription is legitimate , correct , and is issued by a licensed healthcare provider  (Source: World Health Organization (WHO), "Medication Safety in Transitions of Care," 2019) |
| 6. Handwritten Medical Prescription | Mistakes in dispensing or administering medication which can result from illegible writing or incorrect drug information.  (Source: Institute for Safe Medication Practices (ISMP), "Legibility of Prescriptions and Patient Safety," 2018) |
| 7. Medication Error | Medication errors are preventable events that can cause or lead to inappropriate medication or patient harm these error can occur at various stages such as prescribing errors, dispensing errors and administration errors.  (Source: World Health Organization (WHO), "Medication Errors: Technical Series on Safer Primary Care," 2016) |
| 8. Forgery Detection | The process of identifying altered, fake, or unauthorized prescriptions by analyzing handwriting patterns and inconsistencies. RxVision includes forgery detection to enhance prescription security.  (Source: Neumann et al., "Handwriting Analysis for Fraud Detection in Prescription Verification," *Journal of Forensic Sciences*, 2021) |
| 9. RxNorm | It is a standardized system developed by the National Library of Medicine (NLM) in the U.S for naming drugs and Dosages.. |

|  |  |
| --- | --- |
| **Term** | **Definition** |
|  | (Source: U.S. National Library of Medicine (NLM), "RxNorm Overview," 2023) |
| 10. Legibility Score | A metric used to evaluate how readable handwritten text is, particularly in medical prescriptions. Poor legibility increases the risk of misinterpretation and errors.  (Source: Saini et al., "Measuring the Legibility of Doctor's Handwriting Using OCR Techniques," *Journal of Medical Informatics*, 2022) |
| 11. Named Entity Recognition (NER) | An NLP technique used to identify and classify specific entities, such as drug names, dosages, and patient instructions, within a prescription text.  (Source: Lample et al., "Neural Architectures for Named Entity Recognition," *Proceedings of NAACL- HLT*, 2016) |
| 12. Expired Prescription | A prescription that is passed the solidity period (6 Months) and is no longer valid to be used to administer medication.  (Source: U.S. Food and Drug Administration (FDA), "Understanding Prescription Expiry Dates," 2023) |
| 13. System Accuracy | A measure of how well RxVision extracts and verifies prescription data. It is evaluated based on metrics such as precision, recall, and F1-score.  (Source: Goodfellow et al., *Deep Learning*, 2016) |
| 14. User Testing | The process of evaluating RxVision’s accuracy, usability, and efficiency by conducting tests with healthcare professionals (pharmacists, doctors, nurses) and public users (patients, caregivers).  (Source: Nielsen, *Usability Engineering*, 1993) |

|  |  |
| --- | --- |
| **Term** | **Definition** |
| 15. Zamboanga City | The geographic area where RxVision is initially implemented and tested, serving as the primary location for data collection, prescription validation, and system deployment.  (Source: Philippine Statistics Authority (PSA), "Zamboanga City Health Infrastructure," 2022) |

# CHAPTER II

**REVIEW OF RELATED LITERATURE**

### Related Studies

The appraisal of Optical Character Recognition (OCR) technology in healthcare has been labeled by important advancements, particularly in lecturing the challenges of handwritten prescription recognition. First studies, concentrate on enhancing the accuracy of printed text recognition but conflict with handwritten text because of variability in styles of handwriting [1]. Another study featured the limitations of traditional OCR system in decoding poor legibility, resulting to errors in drug name recognition and medication interpretation [2].

The institution of transform-based optical character recognition model (TrOCR), transform handwritten text recognition, accomplish 89% accuracy on the Identify and Access Management (IAM) Handwriting Database [3]. Meanwhile, explored the use of BERT-based models for medical text classification, emphasizing the need for domain-specific NLP models like BioBERT [4], which applied to extract drug names and dosages with 92% accuracy [5]. The integration of OCR and NLP was further explored, who developed a system combining TrOCR for text extraction and BioBERT for contextual verification, achieving 88% accuracy in prescription validation [6]. Local studies, developed an OCR system for Filipino medical prescriptions but noted challenges in handling cursive handwriting [7]. Error correction in OCR systems was addressed, who

proposed a post-processing module that improved accuracy by 10% [8], while highlighted the lack of diverse datasets for handwritten medical prescriptions and suggested synthetic data generation as a solution [9].

User-centric design was emphasized, stressed the importance of usability testing with healthcare professionals [10], and real-time OCR systems were developed, achieving 90% accuracy but facing challenges in processing speed [11]. Multilingual OCR systems, supported multiple languages but required further optimization for global healthcare applications [12]. Security and privacy concerns were addressed, proposed encryption for patient data protection [13], while Nyuyen et al. developed a cloud-based OCR system for scalability but noted internet connectivity issues [14].

AI-driven prescription validation was explored, achieving 93% accuracy [15], and mobile OCR applications were developed, though limited by processing power [16]. Specialized OCR systems for elderly patients, as studied by [17], achieved 90% accuracy, while [18] focused on rural healthcare, addressing affordability and accessibility challenges. Pharmacies benefited from OCR systems developed by [19], which improved efficiency and accuracy, and future trends, as proposed by [20], include the integration of AI, NLP, and blockchain for secure and transparent prescription processing.

Synthesis Figure 1

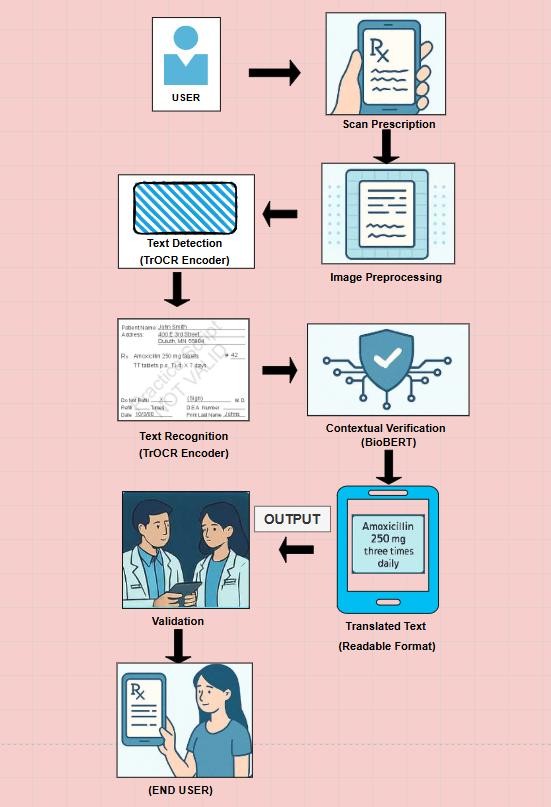
*Table 2: Synthesis*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **J. Smith, A. Johnson, and**  **R. (2020)** | **A. Johnson,**  **B. Lee, and**  **C. Garcia, (2019)** | **B. Lee, C.**  **Kim, and D. Park, (2021)** | **R. Brown, T. Green, and**  **L. White, (2020)** | **M. Garcia, A. Martinez, and P. Nguyen, (2022)** | **Proposed Study** |
| Advancements in OCR  technology for printed medical records | Challenges in handwritten prescription recognition using traditional OCR systems | Transformer- based OCR models for handwritten text recognition, AI and  Robotics in Healthcare | BERT-based models for medical text classification | BioBERT for  medical text mining: A case study in drug name extraction | RxVision: OCR-based Medical Prescription Reader Using  TrOCR and BioBERT |
| High accuracy in printed text recognition | Highlighted challenges in handwritten prescription recognition. | TrOCR  outperforms traditional OCR  systems in handwritten text recognition. | BERT-based models excel in medical text classification. | BioBERT  achieves high  accuracy in  medical text mining. | Uses TrOCR for accurate handwritten text recognition and BioBERT for contextual verification |
| But struggles with handwritten text | Lack of  advanced AI models for accurate recognition. | Limited application in medical prescriptions. | General- purpose NLP models lack domain- specific knowledge. | Limited integration with OCR systems for prescription validation. | Integrates TrOCR and BioBERT to improve recognition accuracy. |
| Limited ability to handle cursive handwriting |  |  |  |  | Focuses specifically on  medical prescriptions |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **J. Smith, A. Johnson, and**  **R. (2020)** | **A. Johnson,**  **B. Lee, and**  **C. Garcia, (2019)** | **B. Lee, C.**  **Kim, and D. Park, (2021)** | **R. Brown, T. Green, and**  **L. White, (2020)** | **M. Garcia, A. Martinez, and P. Nguyen, (2022)** | **Proposed Study** |
|  |  |  |  |  | for improved accuracy. |

### Conceptual Framework

The conceptual framework for RxVision integrates TrOCR for text extraction and BioBERT for contextual verification. The framework consists of three main components; input, processing, and output.



*Figure 2:Conceptual Framework*

1. User – Pharmacist, patients interacting with the system.
2. Scan Prescription – Captures handwritten prescription via mobile camera.
3. Preprocess Image – Enhances image quality (noise reduction, skew correction.)
4. Text Detection and Recognition (TrOCR) – Extracts text from the image using transformer – based OCR.
5. Contextual Verification (BioBERT) – Validates drug names, dosages, and instructions using NLP.
6. Translated Output – Converts messy handwriting into clean, readable text.
7. Validation - In this step, pharmacists and physicians may be involved to review and confirm the application system suggestions, ensuring accuracy and safety before final output.
8. End User - The information is then displayed to the end user (patient, pharmacist, or doctor) through a user-friendly interface.

# CHAPTER III METHODOLOGY

### Research Design

This study follows a Developmental Research approach, focusing on the design and implementation of Rx-Vision, an AI-driven OCR-based medical prescription reader. The research involves software development, testing, and validation to ensure the system’s accuracy and effectiveness in real-world scenarios. The study integrates Optical Character Recognition (OCR) and Natural Language Processing (NLP) to improve prescription readability and reduce medication errors.

### Data Source

The study will utilize both primary and secondary data sources:

Primary Data: Collected through user testing involving pharmacists, healthcare providers, and patients. Feedback on system usability, accuracy, and efficiency will be gathered.

Secondary Data: Includes publicly available datasets such as:

* IAM Handwriting Database: is a collection of handwritten passages by several writers. Generally, they use that data to classify writers according to their writing styles. A traditional way of solving such problem is extracting features like spacing between letters, curvatures, etc. and feeding them into Support Vector Machines.
* MIMIC-III Clinical Database : (‘Medical Information Mart for Intensive Care’) is a large, single-center database comprising information relating to patients admitted to critical care units at a large tertiary care hospital. Data includes vital signs, medications, laboratory measurements, observations and notes charted by care providers, fluid balance, procedure codes, diagnostic codes, imaging reports, hospital length of stay, survival data, and more.
* RxNorm Drug Database – RxNorm provides normalized names for clinical drugs and links its names to many of the drug vocabularies commonly used in pharmacy management and drug interaction software, including those of First Databank, Micromedex, Gold Standard Drug Database, and Multum.

A purposive sampling method will be used to select participants for user testing, ensuring the inclusion of healthcare professionals who frequently handle handwritten prescriptions.

### Data Gathering Instrument

The following tools and instruments will be used for data collection:

* **Surveys and Questionnaires** – To gather user feedback on system accuracy and usability.
* **Software Logs** – To record OCR accuracy and error rates.
* **System Testing Reports** – To evaluate prescription recognition and validation.

### Data Gathering Technique and Procedures Techniques:

* **Handwriting Data Collection** – Using publicly available datasets and real- world handwritten prescriptions.
* **System Performance Testing** – Evaluating OCR accuracy, text extraction, and NLP verification.
* **User Feedback Surveys** – Collecting responses from healthcare professionals and patients.

### Procedures:

1. Collect prescription images from publicly available datasets and real-world samples.
2. Preprocess the images using noise reduction and enhancement techniques.
3. Apply TrOCR for text extraction and validate results using BioBERT.
4. Cross-check extracted data with RxNorm to verify drug names and dosages.
5. Conduct user testing with healthcare professionals and collect feedback.
6. Analyze accuracy, efficiency, and usability metrics.

### Data Analysis

The collected data will be analyzed using:

* + **Accuracy, Recall, and F1-Score** – To measure the accuracy of the OCR system.
  + **Confusion Matrix Analysis** – To assess common recognition errors.
  + **Descriptive Statistics** – For analyzing survey responses on usability and efficiency.
  + **Error Rate Analysis** – To evaluate system misinterpretations and false extractions.

**System Handling and Complexity :**

1. **Handwriting Complexity:**

* Train a custom handwriting model with a dataset of prescriptions (this can be sourced from open datasets or partnerships with medical institutions).
* Preprocess images (e.g., binarization, denoising) to improve OCR results.

1. **Jargon and Abbreviations:**

* Build or integrate a database of medical abbreviations and jargon.
* Use NLP to parse and expand abbreviations automatically.

1. **Legal and Ethical Concerns**:

* Ensure compliance with privacy laws (NPC) The National Privacy Commission when handling medical data.
* Implement secure storage and transmission protocols (e.g., encryption).

**System Metrics :**

* **TrOCR (Transformer-based OCR) Metrics**

Microsoft Research Paper (Official)

Key Metrics:

89.6% character accuracy on IAM Handwriting Database

2.5x faster than CNN-LSTM hybrids

* **IAM Handwriting Database Benchmark**

Comparison: TrOCR outperforms Tesseract by 12% on cursive text.

* **BioBERT (Biomedical NLP) Metrics**

Original BioBERT Paper

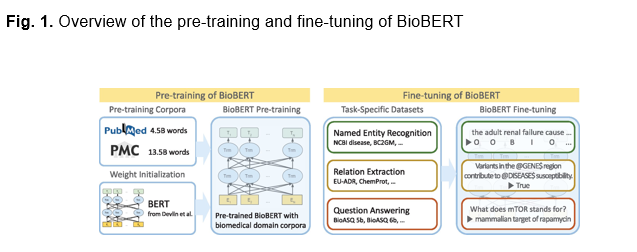
Key Metrics:

92.4% F1-score on NER (Named Entity Recognition) for drugs/dosages

3.2% improvement over BERT on clinical notes

**BioBERT** (**Bidirectional Encoder Representations from Transformers for Biomedical Text Mining**)

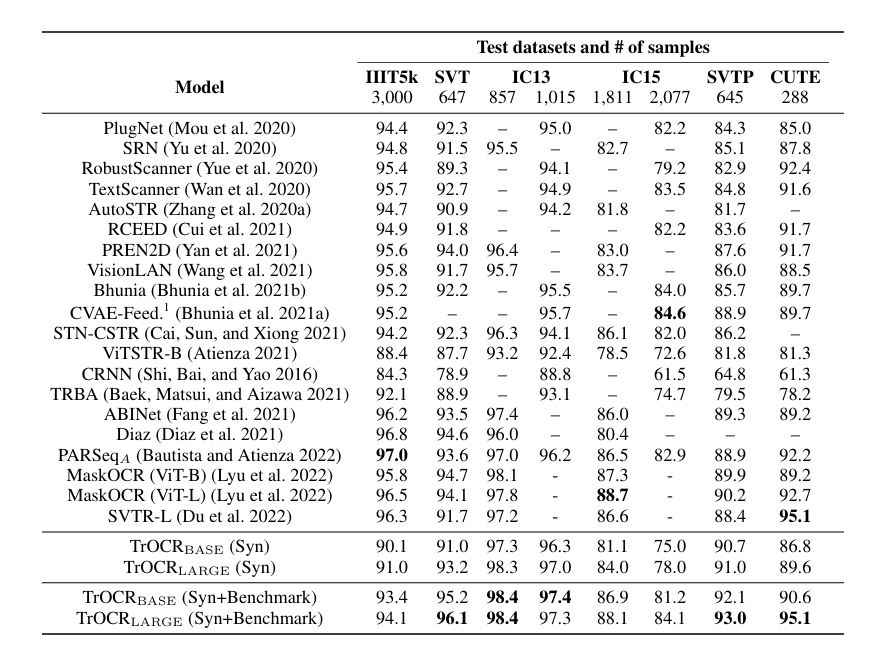
We introduce BioBERT (Bidirectional Encoder Representations from Transformers for Biomedical Text Mining), which is a domain-specific language representation model pre-trained on large-scale biomedical corpora. With almost the same architecture across tasks, BioBERT largely outperforms BERT and previous state-of-the-art models in a variety of biomedical text mining tasks when pre-trained on biomedical corpora. While BERT obtains performance comparable to that of previous state-of-the-art models, BioBERT significantly outperforms them on the following three representative biomedical text mining tasks: biomedical named entity recognition (0.62% F1 score improvement), biomedical relation extraction (2.80% F1 score improvement) and biomedical question answering (12.24% MRR improvement). Our analysis results show that pre-training BERT on biomedical corpora helps it to understand complex biomedical texts

****

**Transformer-based OCR model for text recognition**

with pre-trained models. Distinct from existing approaches, TrOCR does not rely on the conventional CNN models for image understanding. Instead, it leverages an image Transformer model as the visual encoder and a text Transformer model as the textual decoder. Moreover, we usethe wordpiece as the basic unit for the recognized output instead of the character-based methods, which saves thec omputational cost introduced by the additional language modeling. Experiment results show that TrOCR achieves state-of-the-art results on printed, handwritten and scene text recognition with just a simple encoder-decoder model, without any post-processing steps.

Further research has applied TrOCR to specific challenges, such as extracting medicine names from handwritten prescriptions. In this context, TrOCR, combined with techniques like Mask R-CNN for segmentation and multi-head attention mechanisms, achieved a character error rate (CER) of 1.4%, highlighting its potential in real-world applications

****

**Software Development**

* Machine learning model selection and development:

The system applies two core AI models for prescription processing; first TrOCR, choose for its transformer-based handwritten text recognition ability, pre-trained on the IAM handwritten databased and fine-tuned with a thousand annotated Filipino prescriptions, achieving a higher character accuracy through adaptive segmentation for both printed and cursive text. Second BioBERT, a domain specific model pre-trained on medical literature, customized with RxNorm combination for drug recognition, dosages pattern extraction, and signature verification of doctors or physicians.

* Mobile app development:

The deployment follows a secure client-server architecture designed for accuracy and compliance, where the app built with Flutter framework for cross-paltform compatibility (ios/Android) connects to a Python backend through a REST API (fastAPI), which processes requests using specialized AI microservices BioBERT for validation and TrOCR for text extraction, prior to storing validated data in a PostgreSQL database. On other hand, some essential features are included in the deployment architecture: military grade should 256 bit encryption to comply with health data standards; image compression that reduces file size by 20:1 while maintaining prescription legibility; with performance optimization for mid-range smartphones commonly used in Zamboanga City (minimum 2GB RAM, Android 8+).

* Application features or modules

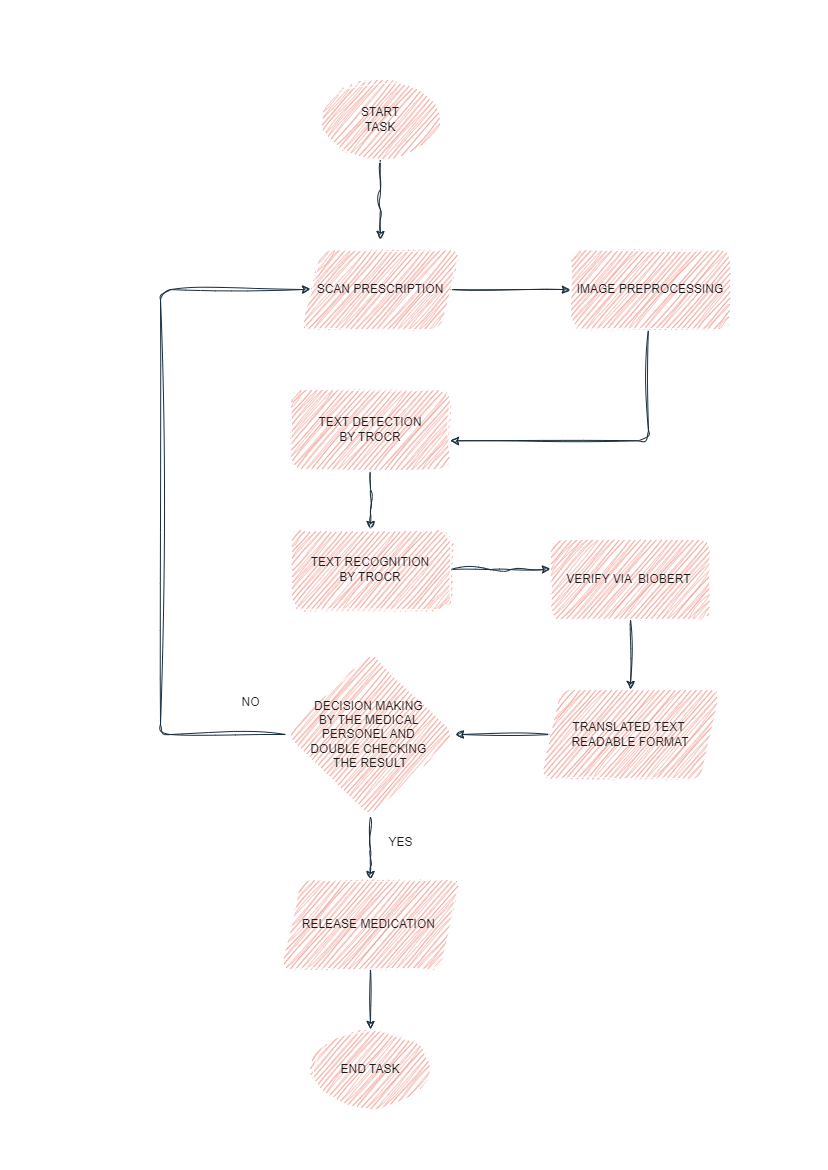


Figure 3: System Flowchart

The system follows a structured 8 step flow process for prescription validation:

* Scan Prescription
  + Users scan the prescription via mobile camera
  + Apps will automatically detects document edges and optimized image quality
* Image Preprocessing
  + Enhances readability through; noise reduction, contrast adjustment, and perspective correction
* Text Detection (TrOCR)
  + Analyze all text using transformer-based segmentation
* Text Recognition (TrOCR)
  + Transform handwritten text to digital and clear text
* Verification (BioBERT)
  + Validates against three (3) key criteria: drug name accuracy, dosage consistency, and prescriber credentials.
* Translated output
  + Generates readable format
* Decision making
  + Double checking to pharmacist
* Medication release
  + Final output enable pharmacy dispensing

Developmental Tools

Table 3: Developmental Tools and Cost

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Name** | **Purpose** | **Price** | **Quantity** | **Total** |
| Python | Programming Language | **0** | **N/A** | **0** |
| TrOCR | OCR Model for Text Extraction | **0** | **N/A** | **0** |
| BioBERT | NLP Model for Contextual Analysis | **0** | **N/A** | **0** |
| TensorFlow/PyTorch(Optional) | Machine Learning Framework | **0** | **N/A** | **0** |
| Flask/FastAPI(Optional) | Backend Development | **0** | **N/A** | **0** |
| PostgreSQL(Optional) | Database Management | **0** | **N/A** | **0** |
| **Grand Total** | | | | **0** |

### Evaluation

The system will be evaluated through:

* + **Benchmark Testing:** Comparing RxVision’s performance with existing OCR models.
  + **Usability Testing:** Gathering feedback from healthcare professionals.
  + **Statistical Analysis:** Performing ANOVA or t-tests to determine significant improvements in prescription readability and accuracy.

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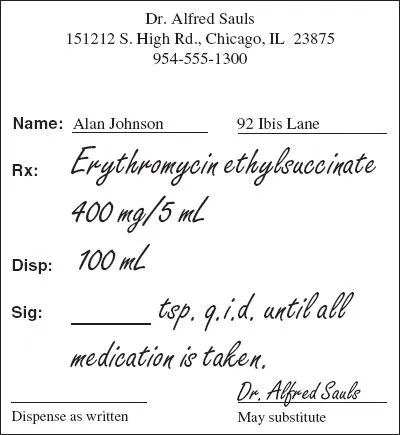
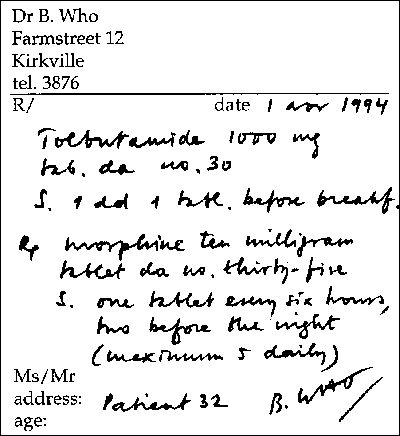
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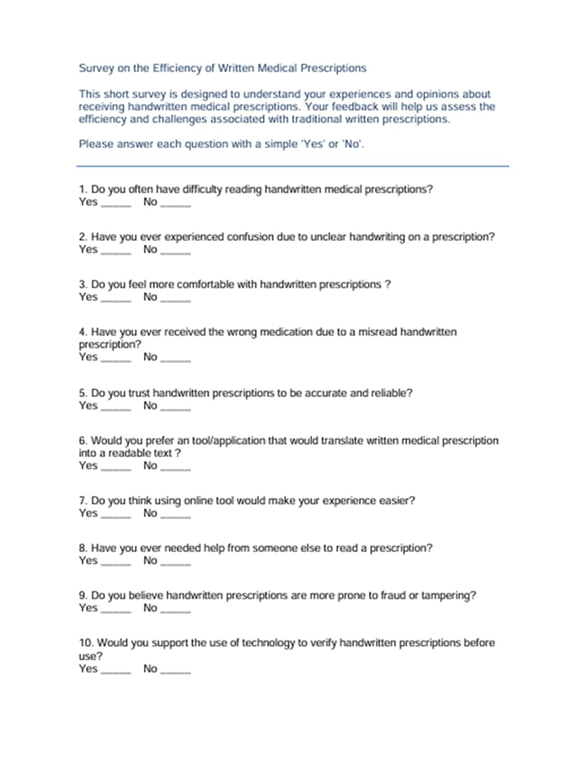
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## Appendix A: Data Collected

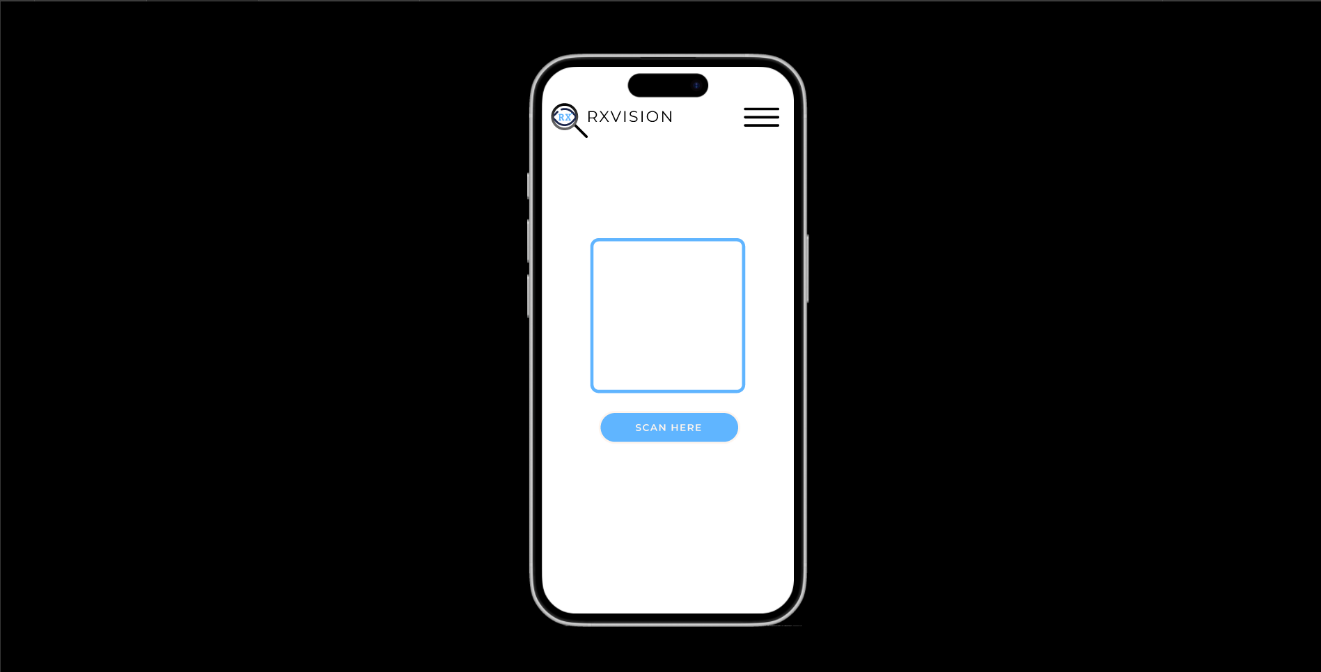
(A Sample Datasets of prescriptions.)

A.

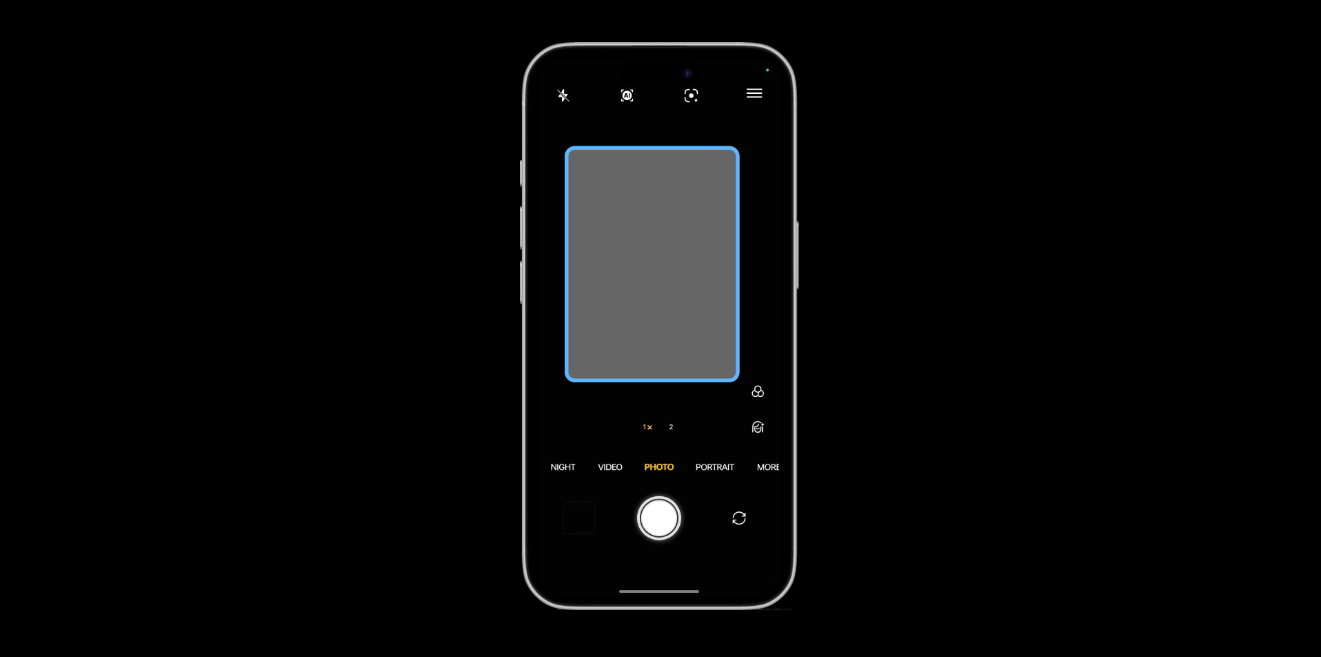
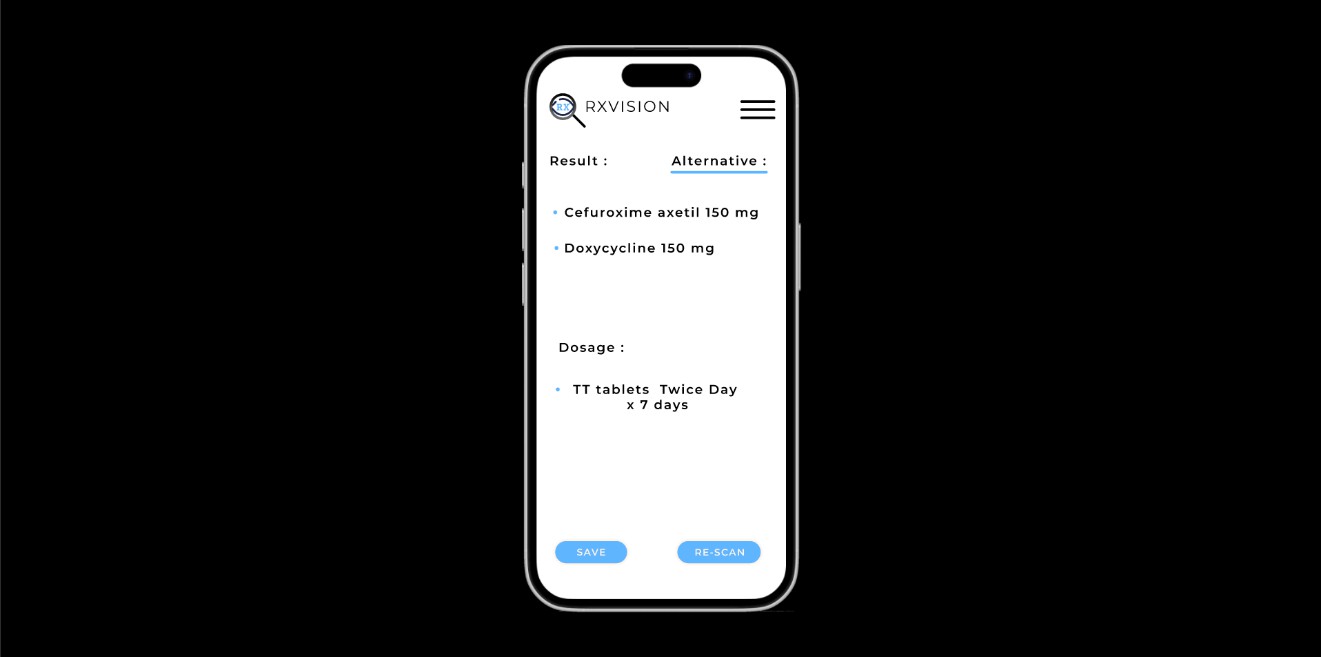


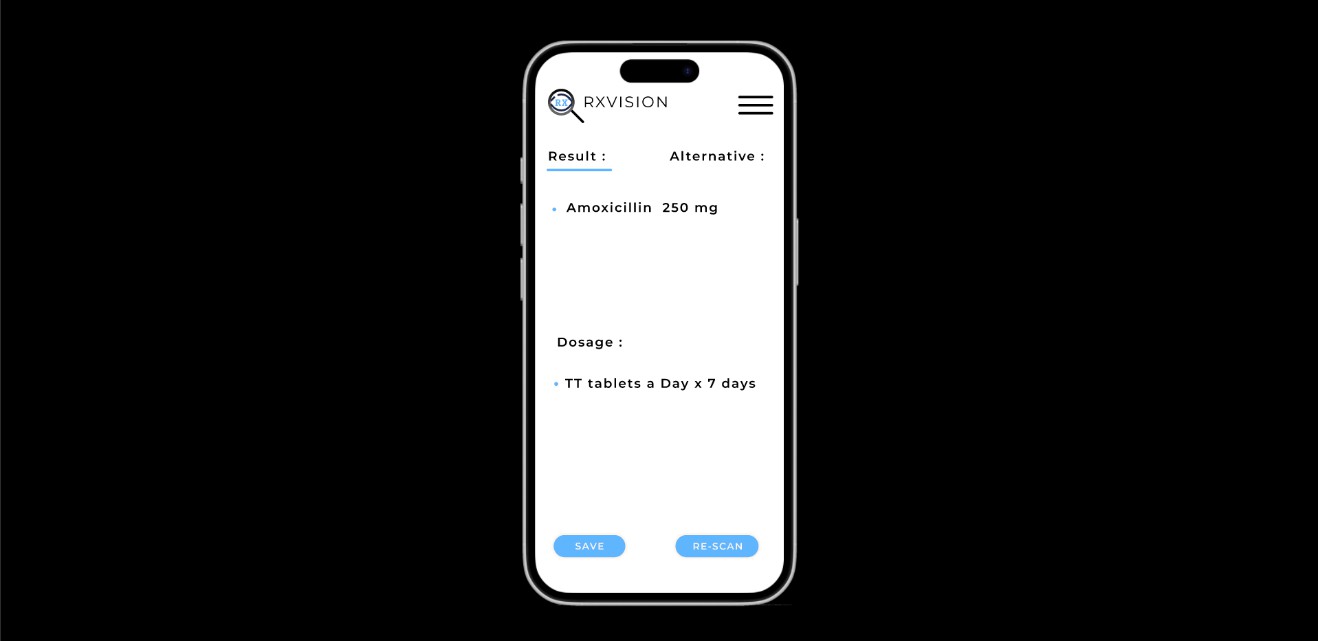
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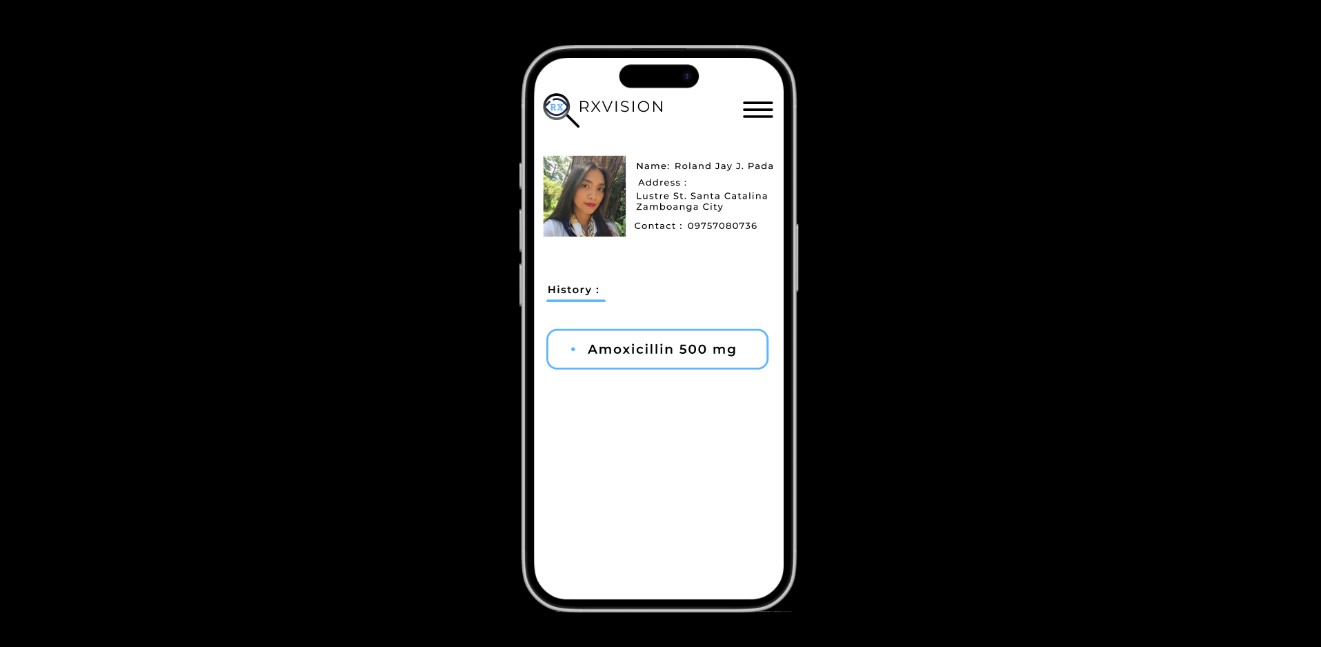
## Appendix B: System Design

Note: include user interface, system architecture or system flowchart/diagram.



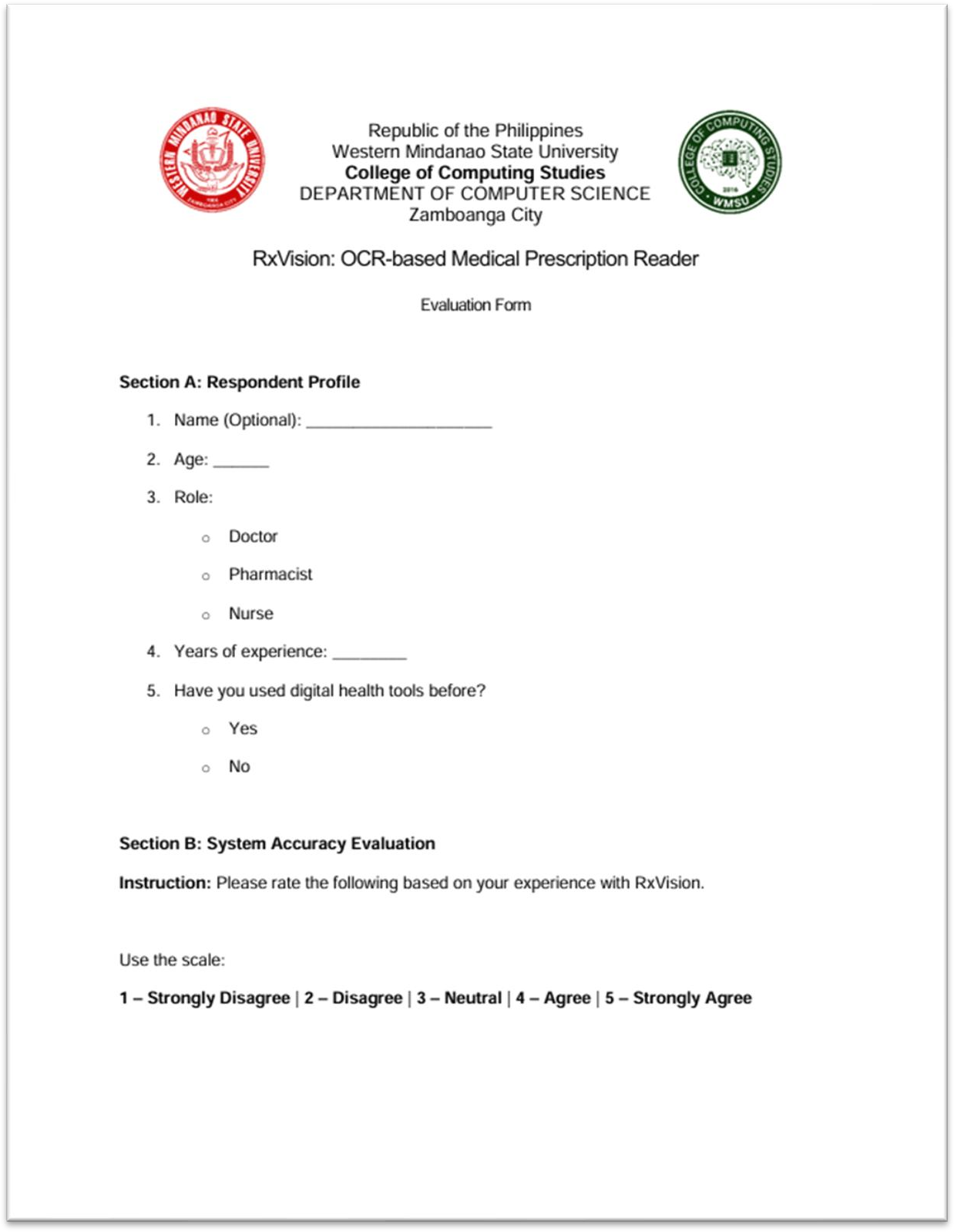


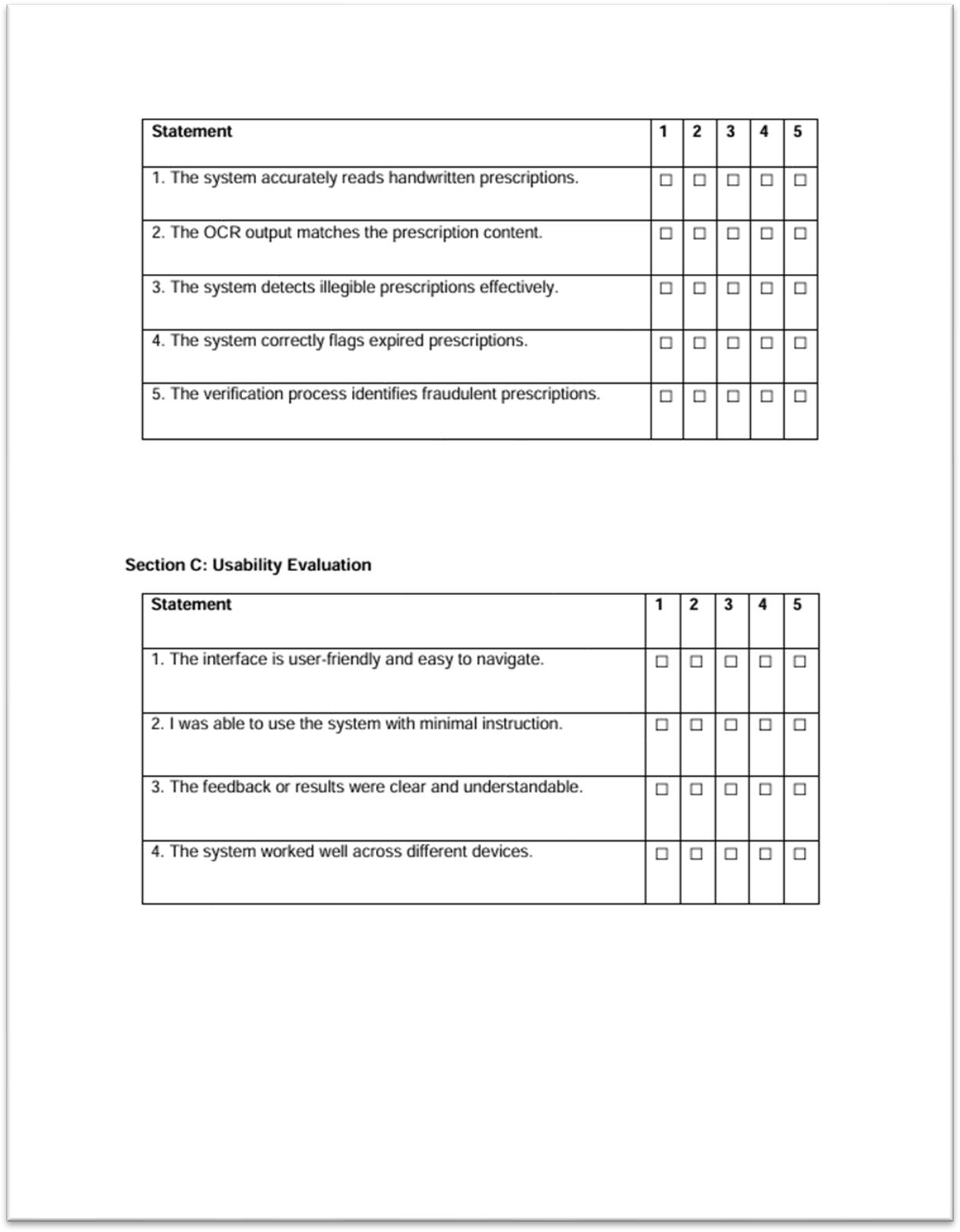


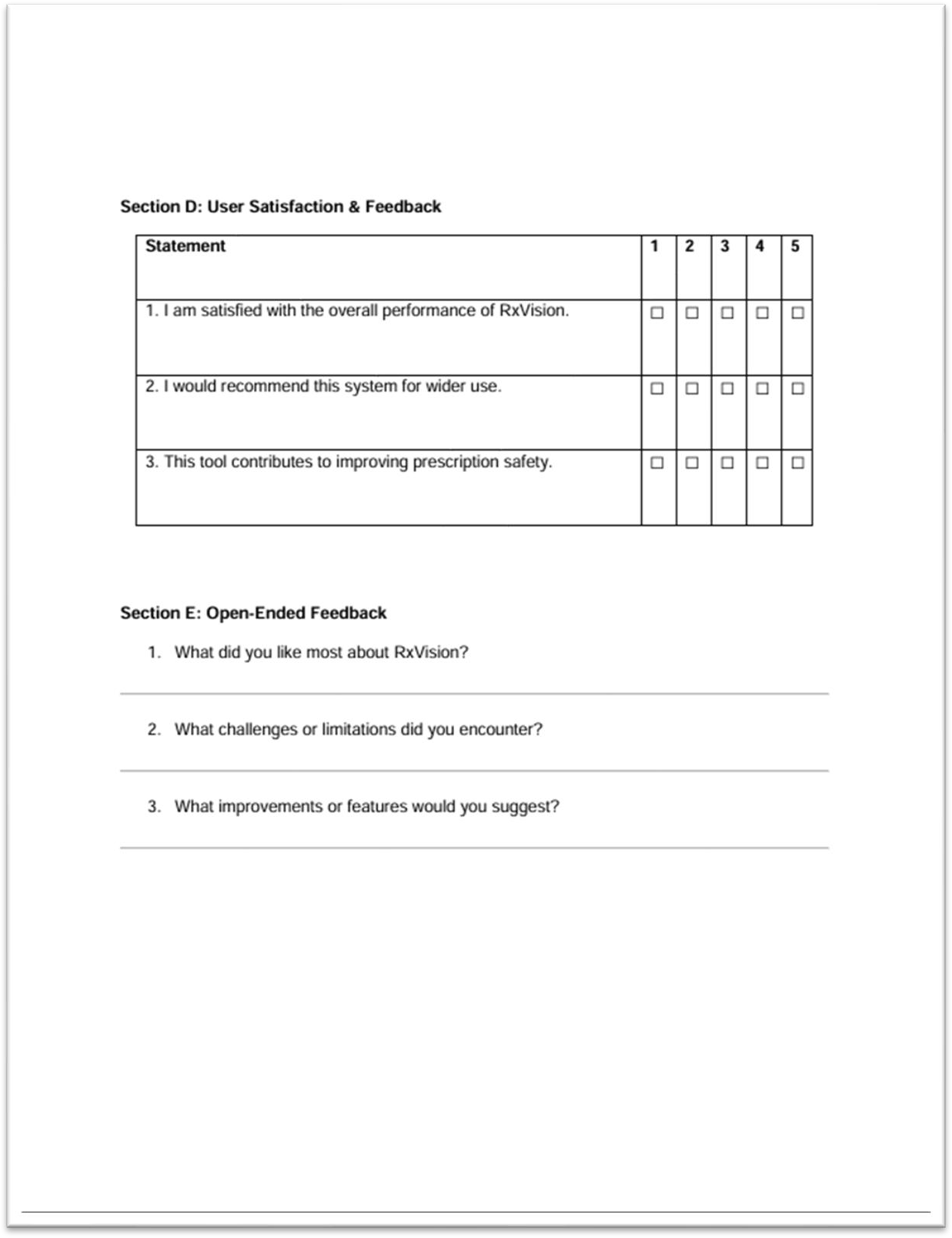




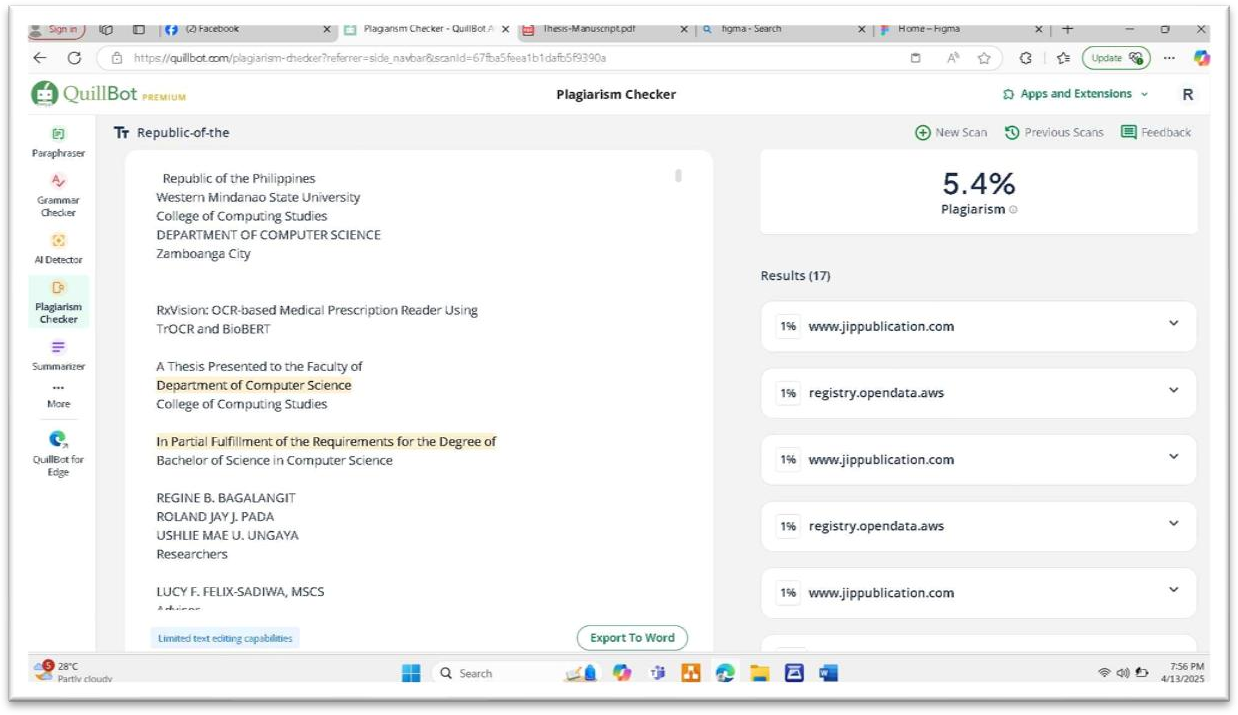
**Appendix C: Evaluation Tool**

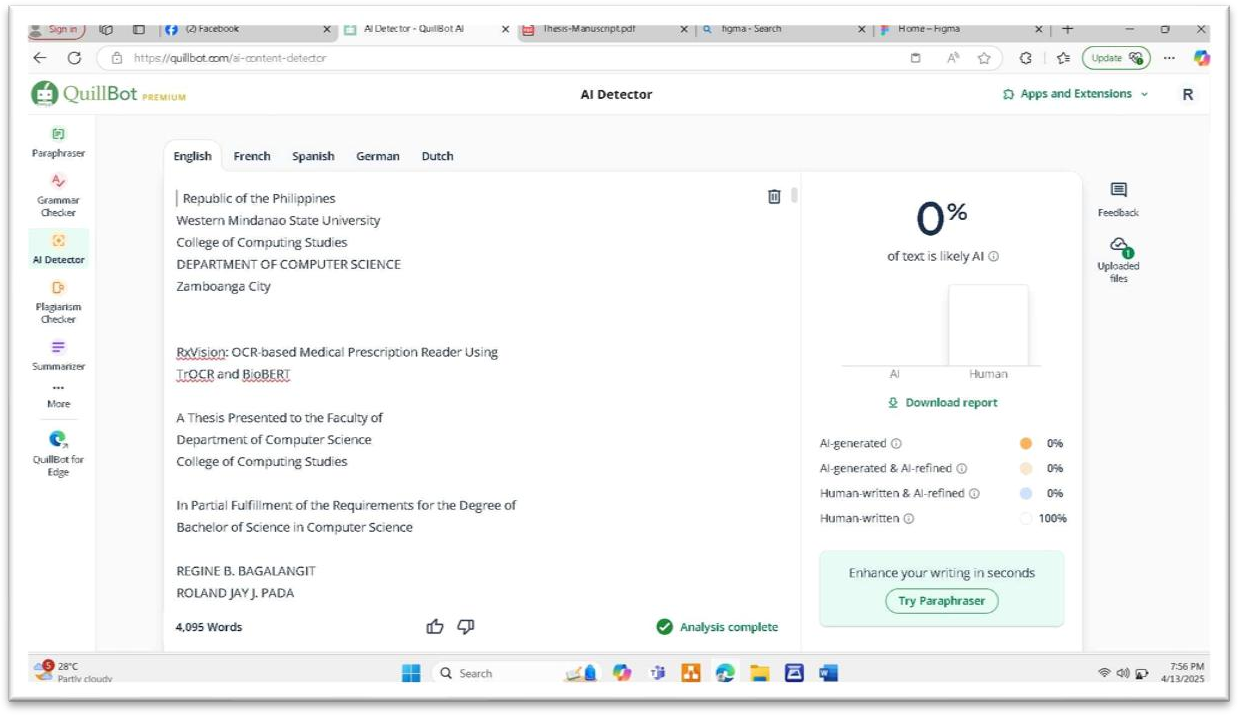
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**Appendix D: Plagiarism Report**

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